Measure and Manage your Product Costs Right – Development and Use of an Extended Axiomatic Design for Cost Modeling

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	Basic concept
X	Input entities
Y	Output entities
x	Input parameters
y	Output parameters
$\hat{y}$	Predicted output variable
F	System structure/design of the real system
f	Model structure/design of the model (system)
m	Metamodel structure/design of the metamodel
$A_{X,Y}$	Design matrix, mapping X to Y
FR	Functional requirement
CM	Component

	State-of-the-art
p_f	Production function
λ	Minimum input resource requirement/production coefficient
q	Realized demand
x	Total input resource requirement
PCb	Benchmark product costs
PCh	Measured product costs
RC	Input resources
RCU	Input resource units
TCU	Total resource units
RCC	Total resource costs
$INTER$	Products' diversity concerning the product mix
$INTRA$	Diversity of products' production technology
CP	Cost pool
s	State
c	Cost state

	Extended Axiomatic Design (EAD)
P	Products
C	Customers
FR	Functional requirements
FRs	Index of functional requirements (#Number of *FR*)
DP	Design parameter
CM	Component
CMs	Index of components (#Number of *CM*)
Π	Profit
$\hat{p}$	Selling price (output)

ρ	Buying price (input)
c_f	Aggregated cost function
Ps	Index of products (#Number of *P*)
Cs	Index of customers (#Number of *C*)
DP	Design parameters
DPs	Index of design parameters (#Number of *DP*)
PV	Process variables (AD)
AV	Activity variables (EAD)
PVs	Index of processes (#Number of *PV*) (AD)
AVs	Index of activities (#Number of *AV*) (EAD)
RC	Resources
RCs	Index of resources (#Number of *RC*)
TRU	Total resource units
OH	Overheads
DC	Direct costs
PCB	Benchmark product costs
PCH	Measured product costs
	Results
ΔPC	Product (variant) cost difference
ΔPPC	Product (variant) production cost difference
ΔTC	Firms' total cost difference
PE	Percentage error
APE	Absolute percentage error
EUCD	Euclidean distance
MPE	Mean percentage error
σ	Standard deviation
R	Market diversity after Gupta & Krishnan (2001)
OD	Targeted performance tier for modularization
Q_VAR	(Customer) demand dispersion
AV_DENS & DENS	Density of the product technology (*CM-PA* sharing)
PA_DENS	Density of the product architecture (*FR-CM* sharing)
UNIT_SHARE	Number of demand proportional processes
RC_VAR	Resource cost dispersion
COSTHIGH	Component unit cost dispersion
CPH	Cost pool building heuristic
CDH	Cost driver selection heuristic
m	Measurement system

List of abbreviations

ABC	Activity-based costing
AD	Axiomatic design
B	Standardized regression coefficients
DFX	Design for X
DIV	Allocation base of product units
DLH	Average direct labor hours
DM	Allocation base of direct material requirement
DMM	Domain mapping matrix
DSM	Design structure matrix
EAD	Extended axiomatic design
F-value	F-value from an ANOVA type III
LCC	Life cycle costing
M&S	Modeling and simulation
MCU	Main controller unit
NPD	New product development
NUAM	Predetermined non-unit-level measures
QFD	Quality function deployment
TCO	Total cost of ownership
TDABC	Time-driven ABC
TVC	‚Traditional‘ volume-based costing
UAM	Predetermined unit-level measures
VIF	Variance inflation factor
η^2	Eta-squared

1. Introduction

1.1 Research motivation

This thesis examines the measurement and management of product costs to support knowledge and guidance of the notion of competitive advantage of Porter (1985a, 1985b). The development of competitive advantage through differentiation is continuously worsening owing to increasing competition (D'aveni, 2010). When business models solely rely on “comfort zones of differentiation”, they may lose market share. As a result, firms tend to increase their product variety to meet the needs of more customers and raise profits. However, such a strategy can lead to growing costs (Kekre & Srinivasan, 1990), and this emphasizes the importance of cost-effectiveness - despite differentiation - for being profitable in the long run. Hence, firms are forced to offer a product variety at reasonable costs, which may be challenging in practice. Given the significance of cost research, this thesis extensively formalizes and models firms to analyze product cost measurement and management.

Expectations of today’s product cost measurement are high because of increasing information technology capabilities and competition. Cost accounting systems are a common instrument for measuring general resource costs in firms as well as products’ resource consumption and the related expenses. No matter whether monitoring product development or material procurement, cost data facilitate daily decision-making in the value chain. Unfortunately, product cost measurement still contains errors. Specifically, firms’ complexity impairs the full and error-free measurement of all usages, which makes full measurement almost infeasible and often too costly.[1] These errors diffuse into final product cost information and affect cost-based decision-making on such factors as pricing, capacity planning, performance evaluation, inventory management, profitability analysis, and classical cost evaluation (Labro, 2019; Labro & Dierynck, 2018). The economic consequence of erroneous cost information depends on the context and can be more or less severe. Therefore, although recommendations point to the usage of complex costing systems, a balanced strategy between sufficient accuracy and fewer efforts is necessary in practice.

Product cost management concerns resource commitment decisions as well as the selection of alternative cost-effective production technologies (Anderson & Dekker, 2009a). Planning product programs with production technology and the necessary capacities result in the “grand program” of firms that shatters in many sub-decisions into departments such as marketing, production, and development. The high number of departments shows that cost management decisions are less focused, and this makes

[1] The terms of diversity, heterogeneity, and complexity are used interchangeably throughout this thesis. Accounting and economic studies predominantly apply diversity and heterogeneity (Abernethy, Lillis, Brownel, & Carter, 2001; Anderson, 1995; Gupta, 1993; Labro & Vanhoucke, 2008). Engineering and operations management use complexity in the same sense (ElMaraghy, ElMaraghy, Tomiyama, & Monostori, 2012; Guenov, 2002; Meyer, Meßerschmidt, & Mertens, 2019).

it difficult to take integrated and deliberate actions. Consequently, cost management refers to more strategic levels (Shank & Govindarajan, 1993) for its implementation; however, this requires long time commitments in resources and production technology. This long-term perspective is particularly decisive when later adjustments are immensely costly and narrow the space of erroneous decisions. Hence, many trade-offs in product cost measurement and measurement have a relevant impact on the competitiveness and long-term success of firms.

1.2 Problem statement and objectives

Product costs reflect the aggregated consumption of production factors weighted by their respective input prices (Balakrishnan, Labro, & Sivaramakrishnan, 2012a).[2] Costing systems aim to provide information about products' resource usage along the value chain (Horngren, Datar, & Raja, 2014), where managers use the resulting cost information for a myriad of decisions (Labro, 2019; Labro & Dierynck, 2018). By contrast, managing product costs aims to deliberately influence the resource and production function in product-based planning (Blocher, Stout, Juras, & Cokins, 2012; Krause & Gebhardt, 2018). In sum, both cost measurement and cost management are mandatory to be cost-effective and develop a competitive advantage in this area, as shown by Porter (1985a, 1985b). Unfortunately, measuring and managing product costs "right" is challenging because of their unobservable and interdisciplinary nature.

First, firms' trade-off between measurement efforts and the resulting accuracy remains under discussion (Balakrishnan et al., 2011; Hoozée & Hansen, 2018; Labro & Vanhoucke, 2007, 2008), and conclusive evidence for the "right" cost system design choices is lacking (Al-Omiri & Drury, 2007; Drury & Tayles, 2005; Schoute, 2009). Complex costing systems such as activity-based costing (ABC) systems are thought to provide more accurate measurements (Drury, 2015; Horngren et al., 2014); however, their use by firms is limited (Gosselin, 1997, 2006; Jones & Dugdale, 2002) compared with simple traditional volume-based costing (TVC) systems (Al-Omiri & Drury, 2007; Cinquini, Collini, Marelli, & Tenucci, 2013; Drury & Tayles, 1994, 2005; Schoute, 2009). In addition, numerical studies have shown that ABC systems do not always provide error-free cost information (Balakrishnan et al., 2011; Christensen & Demski, 1995, 1997, 2003; Labro, 2006, 2019; Labro & Vanhoucke, 2007, 2008; Noreen, 1991), stressing the question mark over appropriate cost system designs. In sum, this thesis reconsiders the inconsistent discussion and findings to contribute new guidance on cost system design choices.

[2] This thesis prefers the wording of products but uses it interchangeably with services, customers, and other potential carriers of costs. This is a common simplification because modeling does not strictly exclude the principles of services (Fandel, 2005,p. 3f.). Following Schmenner (1986), services have specific characteristics for which the study can partially account.

[1] The first objective of this thesis is to examine simple and complex costing approaches among different environmental circumstances that may support guidance and theory in cost system design choices.

Second, neither complex nor simple costing entirely prevents measurement errors (Babad & Balachandran, 1993; Balakrishnan et al., 2011; Datar & Gupta, 1994; Hwang, Evans, & Hegde, 1993), with imprecision, also recognized as noise or error variance (Bloomfield, 2016), underdiscussed in cost research. Although it is intuitive to address the lack of precision (Amershi, Banker, & Datar, 1990; Banker & Datar, 1989; Datar, Kulp, & Lambert, 2001; Feltham & Xie, 1994; IASB, 2018), most costing research has focused on total error and bias (Anand et al., 2017; Balakrishnan et al., 2011; Labro & Vanhoucke, 2007, 2008). Specifically, increasing data collection by firms may change accepted guidance and theory and raise the probability of finding more unpredictable random measurement errors (Cardinaels & Labro, 2008; Mertens & Meyer, 2018). Finally, it seems suitable to evaluate the magnitude and presence as well as the economic consequences of imprecision in cost-based decisions.

[2] The second objective of this thesis is to examine the effects of random measurement errors on imprecision in reported product costs as well as on their economic consequences in decision-making.

Third, there is limited integration of engineering design and economic principles even though both are fundamental to product planning and share the same objective. Product-based planning is the "grand program" of combined product and capacity planning problems (Balakrishnan et al., 2011). Whereas economists focus on product prices and resource commitments when making their decisions, engineers aim to determine firms' engineering based on customers' needs and the functional requirements of the resulting product designs. Although their perspectives are different, their objectives are largely similar. In detail, engineering design considers a large space of possible product designs (Hazelrigg, 1998) to select the best technical opportunity for creating the requested products, while economic questions seek the optimal decisions in pricing as well as in resource and production commitments (Demski, 2008). In sum, both strands rank possible strongly related product-based planning scenarios under different criteria. Consequently, this thesis aims to extend the theory to formalize and model a detailed product perspective including the subsequent production environment under economic information as well as weight the product plan using the economic metrics of price, costs, and profit from resources to customers.

[3] The third objective of this thesis is to connect engineering design principles with neoclassical firm theory to propose a decision-relevant framework that can comprehensively support product-based planning problems.

Lastly, practical cost management strategies aim to make large resource and production function adjustments, where modularization is perceived as a fruitful approach for achieving cost-effectiveness (Wouters & Morales, 2014; Wouters, Morales, Grollmuss, & Scheer, 2016; Wouters & Stadtherr, 2018). Modularization adjusts, reconfigures, and realigns existing commitments and relations in an organization, particularly its production technology (MacDuffie, 2013). Hence, modularization can drastically reduce firms' total costs, regardless of the initial circumstances (Blees, 2011; Farrell & Simpson, 2009; Jacobs, Droge, Vickery, & Calantone, 2011; Jacobs, Vickery, & Droge, 2007; Kipp, 2012; Kumar, Chen, & Simpson, 2008; Marion, Thevenot, & Simpson, 2007; Ripperda & Krause, 2017); however, there is less evidence (Fixson, 2005, 2006) about the drivers and mechanisms of cost-effectiveness concerning the product architecture. On this point, the extended axiomatic design (EAD) from the previous objective addresses the theoretical foundation to thoroughly construct a model-based engineering system (Adams, Hester, Bradley, Meyers, & Keating, 2014; Madni & Sievers, 2018; Ramos, Ferreira, & Barceló, 2012). This engineering model encourages the analysis of actual guidance in modularization referring to the prominent market segmentation grid (Krause et al., 2014; Meyer & Lehnerd, 1997; Otto et al., 2016).

[4] The last objective of this thesis aims to assess cost-effectiveness when modularizing product architectures to support and test decisive drivers and guidance.

Overall, this thesis develops a theory-orientated framework consisting of engineering design and economic theory to examine decision-making in product-based planning **[3]**. The framework supports the identification of cost drivers when modularizing product architectures. Therefore, this thesis proposes general guidance when applying the market segmentation grid in modularization projects **[4]**. Moreover, it claims that the horserace between simple and complex product costing is still entangled and sensitive to cost structure theory **[1]**. To this end, the lack of precision in product cost information is crucial for optimal decision-making because it may yield overconfidence and profit losses **[2]**.

1.3 Structure of this thesis

Figure 1 illustrates the conceptual framework of this thesis. The foundations of modeling and simulation (M&S) as well as product cost measurement and management are presented in Section 2 to clarify the understanding of the basic concepts. Section 3 builds upon Section 2 by outlining the latest research activities in both fields with a slight emphasis on modularization. Both support the formalism of the EAD in Section 4, which provides the foundation for the conceptual and further computational models. Sections 5, 6, and 7 present the results, and Section 8 concludes.

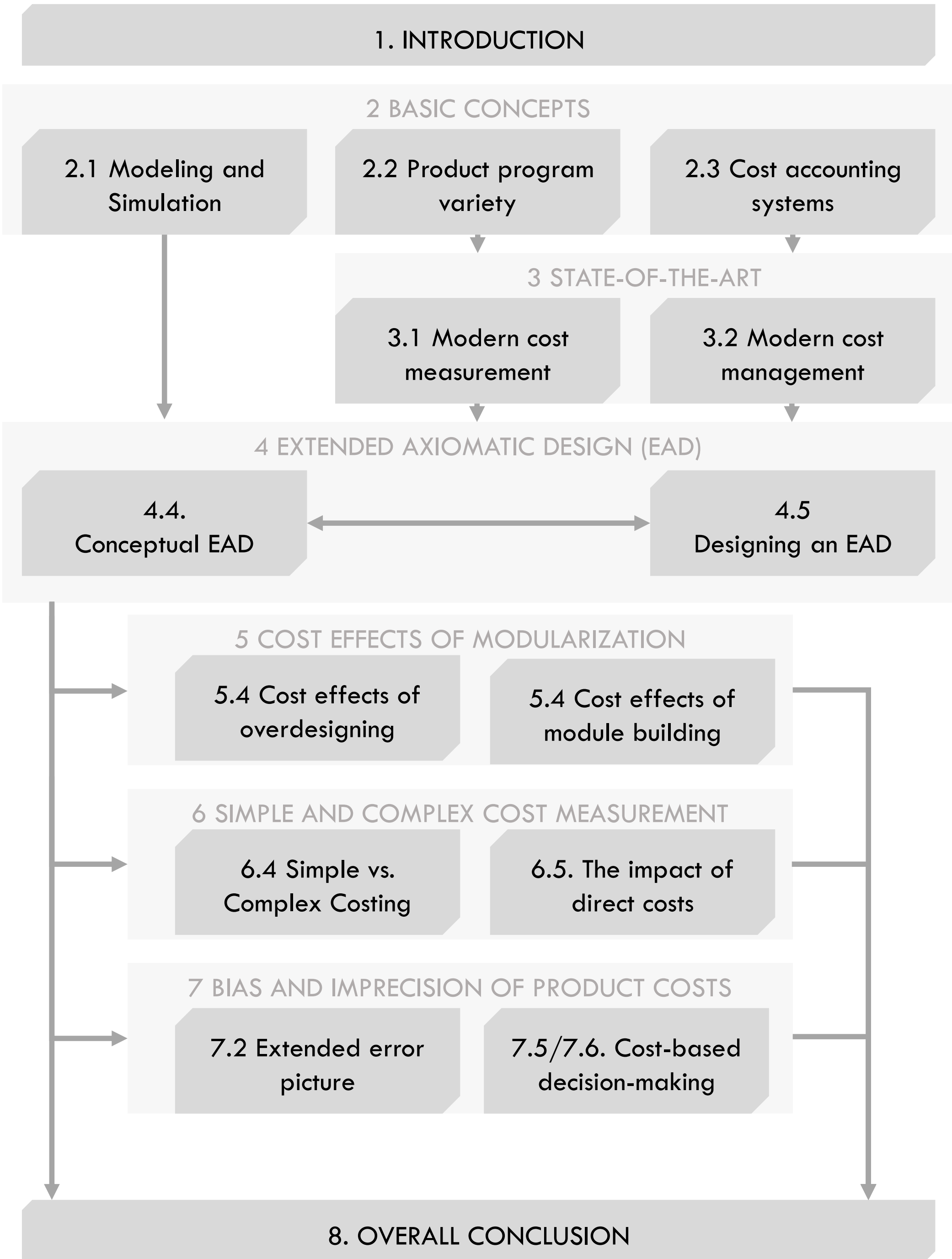


Figure 1: Conceptual structure of this thesis

2. Basic concepts

2.1 Modeling and simulation (M&S)

2.1.1 M&S as a research method

M&S, the main research method in this thesis, primarily refers to the conceptual modeling of problems that will be computerized and hence manipulated while observing the responses (ASME, 2007; Balci, 1994; Harrison, Lin, Carroll, & Carley, 2007; Law, 2014a, 2014b; Oberkampf & Roy, 2010; Sargent, 2013).[3] Studies use M&S to model, test, and develop and elicit causal mechanisms (Balakrishnan & Penno, 2014) in all kinds of fields. Because it is widely acknowledged, it is differently used (Grisar & Meyer, 2015; Hauke, Lorscheid, & Meyer, 2017b; Meyer, Zaggl, & Carley, 2011). While agent-based M&S includes social and behavioral simulations, production and industrial cases apply mixes of Monte Carlo and discrete-event M&S. No matter which approach is used, every M&S study yields an artificial laboratory for testing and manipulating inputs while observing responses.

The advantages of M&S are its capacity to perform experiments despite unobservability and analytical intractability in less time and at lower cost. M&S has long flourished in research (e.g. Shannon, 1975) and is not an exclusive academic method (Clymer, 2009). Over time, it has matured to become an accepted methodology for providing generalizable findings, particularly on questions of theory testing and development (Davis, Eisenhardt, & Bingham, 2007; Harrison et al., 2007). In detail, studies use it to predict and explain outcomes among uncertainty without employing large and costly equipment and in a fraction of the time of real experiments (Law, 2014a). This capability strengthens research investigating unobservable mechanisms by implementing theoretical relations in the computational model.

The physical science community most frequently models phenomena using M&S to mitigate time restrictions and unobservability. M&S discussions in physical science are based on influential theories such as the relativity and mass-energy equivalence of Einstein (1905). Using theories supports conceptual and computational models of space, where numerical explorations foster the investigation of unobservable phenomena. For instance, phenomena such as black holes and galaxy generations are not observable due to the enormous time restrictions. However, M&S allows researchers to explain how galaxies develop (Vogelsberger et al., 2014) and how black holes evolve (Stergioulas, 2009) before empirical observations have been found. Overall, M&S is thus a valid approach for exploring complex phenomena.

Through widespread applications and questions, M&S has built branches for efficiently designing conceptual and computational models, where discrete event, agent-based Monte Carlo as well as hybrid

[3] This research method is not linked to computers per se, but this thesis concentrates on computational M&S.

simulations forms are prominent. For example, agent-based modeling formalizes the actions and rules of individual micro-level behavior by agents that autonomously interact with their environments. These micro-level interactions emerge in a macro-level phenomenon (e.g., socio-technical or socio-ecological systems) (Schulze, Müller, Groeneveld, & Grimm, 2017; Squazzoni, 2012). Discrete event simulation is a stepwise modeling process with actions over time, stages, and events aiming to emulate a flow process (Siebers, Macal, Garnett, Buxton, & Pidd, 2010). For instance, this approach is prominent in investigating production scheduling problems. Monte Carlo simulations use repetition to study uncertain input assumptions while calculating numerous scenarios for analysis. Native applications are associated with risk management in business administration (Grisar & Meyer, 2015). Overall, the presented typology is ideal when many M&S projects belong to hybrid and blended forms.

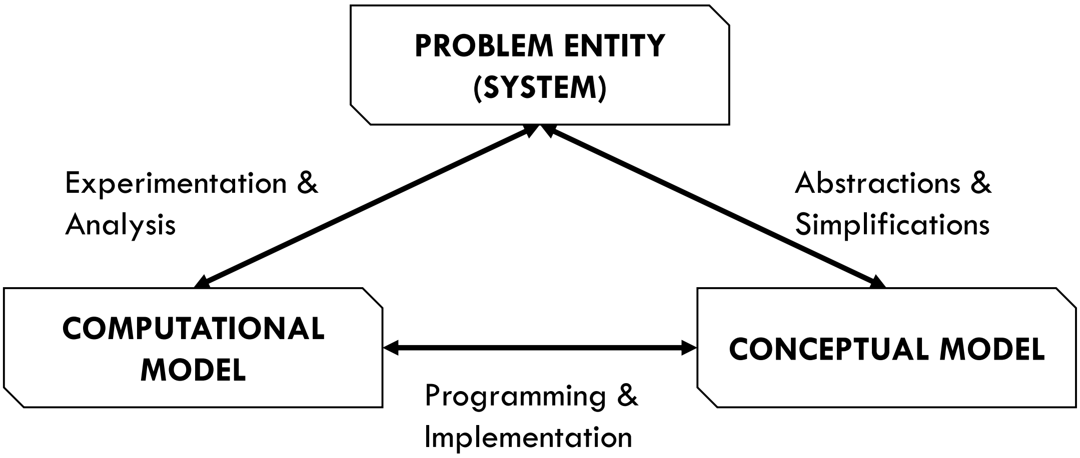


Figure 2: Model development cycle of M&S

Despite the existence of diverse M&S approaches, a generic M&S development process encompasses a problem entity, a conceptual model, and a computational model, as shown in Figure 2 (Balci, 1994; Barth, Meyer, & Spitzner, 2012; Law, 2014a; Robinson, 2008a, 2008b; Sargent, 2013). M&S studies start with a focal research objective or research questions about a system, resulting in a problem entity containing elements, rules, or patterns. During conceptual model development, modelers abstract and simplify the problem entity to its relevant core principles. This model hence exemplifies the relevant elements and interactions concerning the model's problem (Robinson, 2008a, 2008b). Finally, the conceptual model leads to the implementation of a computational model using coding and compiling. The computational model is a virtual laboratory ready to receive manipulations for tracking the responses. By manipulating the input parameters, the model yields outcomes from the implemented rules. The stimulations in the responses are thus observable and useable for statistical analysis and reasoning.

Each M&S study continuously requires verification and validation at each level to sustain models' credibility (Law, 2014a; Sargent, 2013). Although the theoretical M&S development process is linear, it is actually a circle of plausibility checks and remodelings to allow verification and validation. As shown in Figure 2, all arrows are doubled to denote this circularity. This process is closer to M&S development because each stage can have issues such as less substantiated simplifications, programming errors, and missing alignment to the problem. This thesis, therefore, recommends that modelers repeatedly falsify themselves to start a process of rethinking and remodeling. This stepwise process ensures the quality of M&S by verification and validation, which is essential for generating rigorous and credible results as well as conclusive communication (Balci, 1994; Barth et al., 2012; Rand & Rust, 2011; Waldherr & Wijermans, 2013). Overall, M&S projects must supply enough credibility to communicate their conclusions and reasoning.

Regarding reasoning, M&S can be closer to either inductive or deductive principles (Axelrod, 1997, 2006). It can use existing theory such as the general relativity of Einstein (1905) and production theory of Cobb and Douglas (1928) or empirical observations to develop models (Grimm et al., 2005; Hauke, Lorscheid, & Meyer, 2017a; Klügel & Karlsson, 2009). When applying existing strong theory, it swings toward a more deductive conceptual model, where empirical observations lead to more inductive modeling. Both ways affect the conceptual model and determine the potential for reasoning, meaning whether the study will support generalizations through theory testing or offer theory developments, respectively. Indeed, according to discussions (Popper, 1998), M&S is neither strictly inductive nor deductive (Axelrod, 2006). To sum up, M&S supplies ways for analyzing hardly measurable phenomena in complex systems with fewer restrictions in terms of costs and time to test and develop theory (Axelrod, 1997; Conte, 2009; Davis et al., 2007).

2.1.2 Systems, models, and metamodels

Another perspective of M&S study development provides three levels of granularity, namely the real system F (problem entity), the model f (conceptual and/or computational model), and a metamodel m (statistical analysis), as shown in the research process in Figure 3 (Barton, 1998; Barton & Meckesheimer, 2006; Kleijnen & Sargent, 2000).[4] The previous section provided information about the M&S development process, whereas this section illustrates the conceptual granularity in M&S, starting from the problem entity to conceptual and computational modeling toward statistical analysis.

The real system $F(X)=Y$ includes for input X and outputs Y entities as well as functional relationships, known as the design F. Assuming that parts of systems are decomposable, F reflects a more or less complex mechanism designed as an interplay of rules, functions, and entities. Of course, mechanisms are relevant for targeting the problem entity and they start the M&S development process, where abstractions and simplifications then consolidate F to the model f. In this process, only a few

[4] The definition of a model in M&S is subtle. Every study ideally starts with a conceptual model and transfers it into a computational model. The transition between the model also allows for differences because the conceptual model is not necessarily correctly implemented. In practical research, there is sometimes less emphasis on this issue where studies frequently are arguing from the computational level. Preventing this pitfall, modelers should use frameworks or techniques for conceptual modeling (Grimm et al., 2010; Mertens, Lorscheid, & Meyer, 2017; Müller et al., 2013). For simplicity, this stage is ignored in this thesis.

entities X and Y are of particular interest. Therefore, modeling also operationalizes the entities to quantitative inputs x and outputs y. An optional step at the end is the statistical modeling of the model f, which analyzes complex simulation model behavior (Mertens, Lorscheid, & Meyer, 2015). Statistical modeling is prominent in all kinds of fields, where M&S frequently postulates it as metamodeling (Pietzsch et al., 2020). The resulting metamodels surrogate the behavior of the model f and support the reasoning and concluding by predicting or explaining the simulation data x and y. To sum up, Figure 3 illustrates the granularity, and the next paragraphs provide more detailed explanations by exposing the real system F, the model f, and the subsequent statistical modeling m.

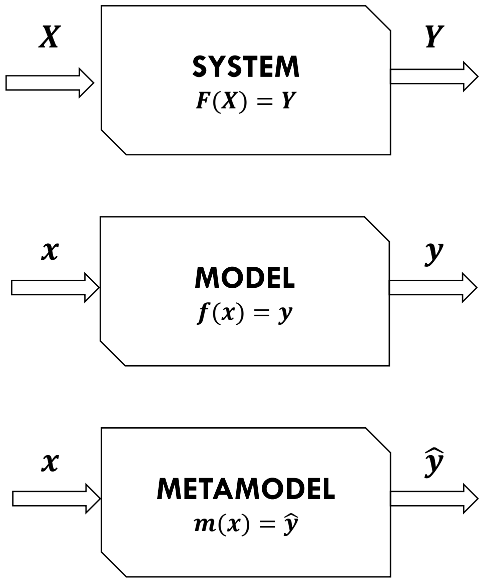


Figure 3: Conceptual overview of the system, model, and metamodel

Systems' skeleton F incorporates a design that reacts with a response Y when receiving inputs from X (Adams et al., 2014; Cook & Wissmann, 2007; Van Gigch, 1991). This definition reflects systems' behavior. The question of the boundaries or limits of a system are not new; they are not absolute but rather depend on the specific context. Further, systems are not necessarily isolated, meaning that their designs and elements are barely decoupled from those of other systems. It is rather the case that the systems contain complex mechanisms with more than one system (An, 2012; Polhill, Filatova, Schlüter, & Voinov, 2016; Werner & McNamara, 2007). This perspective parallels and agrees with Simon (1962), who states in his "philosophy of systems" that systems are interacting compounds embedded in a hierarchical network. Thus, the general input-output transformation $F(X)=Y$ includes a hierarchal network of systems, as illustrated in Figure 4.

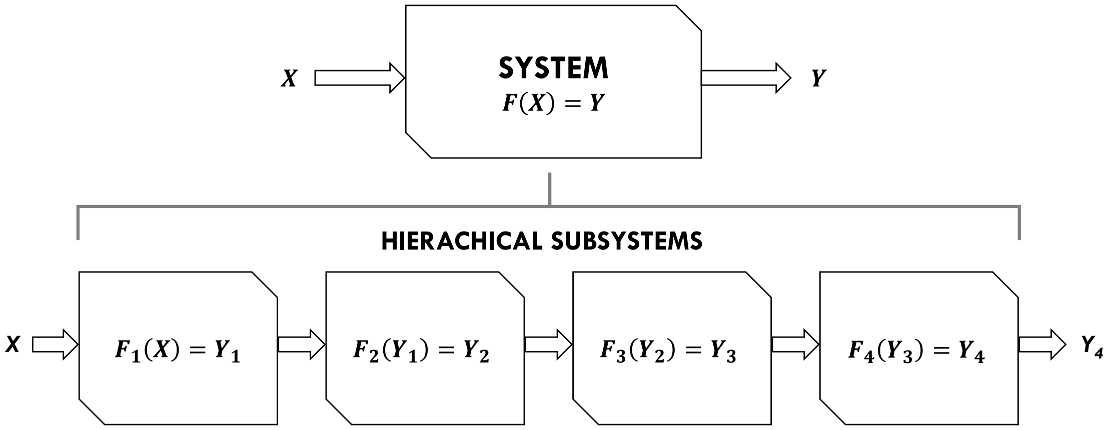


Figure 4: Systems' hierarchical architecture following Simon (1962)

Figure 4 exemplifies a system as a network of subsystems that determines the potential hierarchical structure of a complex system (Simon, 1962). Examples of systems with subsystems are airplanes, military vehicles, organizations, firms, and even social networks (Eppinger & Browning, 2012). This mental model has become the cornerstone of system engineering and model-based engineering (Cook & Wissmann, 2007; Eppinger, Whitney, Smith, & Gebala, 1994; Madni & Sievers, 2018; Ramos et al., 2012). In the context of this thesis, a firm is a complex system with various subsystems such as marketing, development, procurement, operations, and controlling. It may be intuitive, but the more interactions between elements and designs, the larger systems' complexity (Adams et al., 2014; Clymer, 2009; Li & Meerkov, 2009; Simon, 1962). Overall, this thesis determines a system as a hierarchical set of subsystems comprising parameters and functional relationships (Clymer, 2009, p. 4f.).

Modeling the problem system further through abstractions, simplifications, and operationalizations leads us to model *f*. Modeling the real problem system fully is often unnecessary (Epstein, 2008) and even simple models can offer insights (Edmonds & Moss, 2005; Evans et al., 2013; Sanchez & Lucas, 2002). In line with the statement that "all models are wrong" by Box (1976), modeling is an approximation process that should be sufficient for investigating the intended task. Finally, the functional design of *F* thoroughly converges to the model *f*, likewise operationalizing the entities *X* and *Y* to the quantitative parameters *x* and *y*. Then, the model $f(x)=y$ is a surrogate that focuses on the relevant information from the problem system $F(X)=Y$.

Through the abstractions, simplifications, and operationalizations of the problem system, the model does not account for all functions and parameters, which manifests as a deviation term ε. In the ideal case, the model fully reflects the real system yielding no deviation ε between *F* and *f*. However, this is frequently not worthy because neglecting information is essential for modeling. In addition, the occurring deviation ε is not an error per se, as it accounts for the unnecessary variance from the less context-relevant parts of the problem system. In sum, the deviation does not strictly affect the credibility of outcomes, even though a deviation ε exists. Thus, as long as the model fits the relevant context in the problem system, the ε does not disturb the outcome (Pearl, 2009).

Statistical modeling, designed as metamodeling in the M&S context, analyzes simulation model behavior or predicts the simulation data outcome with less computational effort (Mertens et al., 2017). Metamodeling refers to a series of statistical procedures (Gore, Diallo, Lynch, & Padilla, 2017; Kleijnen & Sargent, 2000; Mertens et al., 2015, 2017; Sargent, 1991), where model inputs *x* and outputs *y* serve as a training set for the statistical approximation of the model *f*. This approximation yields a metamodel *m*. A quality criterion of metamodels concerns keeping residuals *e* as low as possible ($y - \hat{y} = e$). When there are no residuals, the metamodel predicts the output behavior completely in the respective experimental design (Barton, 2015; Kleijnen, 2015; Kleijnen & Sargent, 2000).

Figure 5 shows a metamodel's goals regarding statistical principles, where both prediction and explanation cause a contingency for positioning metamodel approaches. When performing statistical analysis, one can pursue predicting or explaining more (Shmueli, 2010; Shmueli & Koppius, 2011). Neuronal networks or parallel distribution processes (Rumelhart, McClelland, & Group, 1987; Weiss, 2000), for instance, are suitable for high predictive capabilities (Rosen & Guharay, 2013). However, they do not easily unveil simulation models' behavior or design in accessible ways. This approach thus aims to explain where metamodels check the outcome to the simulation model *f* (Mertens et al., 2015, 2017). When seeking explanations, a design with its functions is more important than minimizing the residuals. Overall, metamodels are statistically differentiable by employing an explanation and a prediction dimension (Gore et al., 2017; Kleijnen & Sargent, 2000).[5]

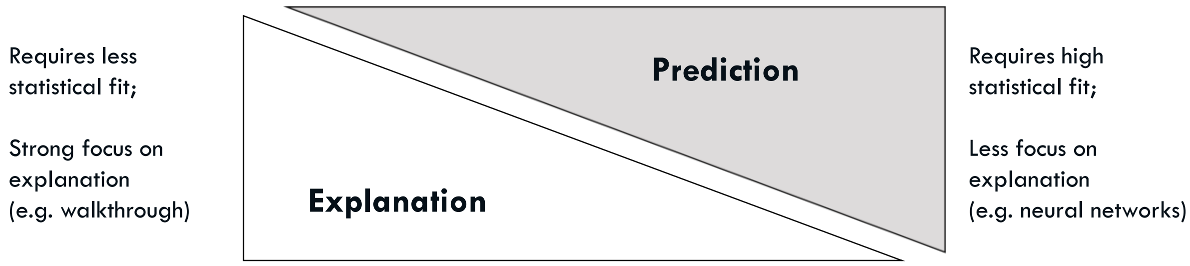


Figure 5: Continuum of metamodels' objectives (Mertens et al., 2015)

To sum up, modelers condense particular problems from systems *F* to models *f*. There is no prerequisite that a model must completely surrogate the real system, but deviations ε can be either sensible or erroneous. On the one hand, simplifications and aggregations support more abstract models that may be more generalizable in their outcomes. Exaggerating toward simplicity, on the other hand, decisive patterns or mechanisms are unintendedly omitted. Finally, this is part of modelers' trade-off between the cost of modeling and model accuracy (Law, 2014b).

[5] This thesis acknowledges the previous differentiation of the four goals of understanding, predicting, optimization, and verification and validation by Kleijnen and Sargent (2000). Their review, which offers insights into the field, concerns the applications of metamodels in simulation studies. Nonetheless, this does not explicitly address the statistical difference of metamodels. In detail, the goals of "understanding" and "verification and validation" aim to '*explain*", whereas "predicting" and "optimization" are linked to "*prediction*".

2.1.3 Design structure matrices (DSMs)

Implementing conceptual models into computational models requires appropriate methods, and this thesis applies DSM modeling, a network modeling technique that has advantages in mathematical, graphical, and computational contexts (Danilovic & Browning, 2007; Eppinger & Browning, 2012; Lindemann, Maurer, & Braun, 2009). Although numerical matrices are by no means rocket science, as stated by Eppinger et al. (1994), their application and continuous development in research and practice have resulted in a mature approach. For instance, DSM modeling has already been used to address problems such as information flows, modularization, interorganizational conflicts, and project management as well as in many engineering projects (Danilovic & Browning, 2007; Eppinger & Browning, 2012; Hölttä-Otto & de Weck, 2007; Lindemann et al., 2009; Sosa, Eppinger, & Rowles, 2003, 2004; Yassine, Whitney, Daleiden, & Lavine, 2003). Whether large-scale projects or simple mappings, DSM modeling thus provides an intuitive approach for modeling, communicating, and visualizing designs of systems without waiving computational suitability.[6]

The previous sections demonstrated that every system owns independent X and dependent Y entities that are sets of arguments called domain D. From a mathematical angle, every input and output contains a possible set of arguments (Kuratowski & Mostowski, 1976) or parameters. For instance, all input entities can be expressed by D_X ($D_X = [X_1, X_2, X_3, \ldots, X_n]$). Nevertheless, instead of using "domains" as the terminology, this thesis follows the M&S terminology of "independent and dependent sets of parameters" to comply with the experiments (Libby, Bloomfield, & Nelson, 2002; Montgomery, 2000). Although both terminologies are interchangeable, this thesis adapts the experiment perspective.

Figure 6 shows an artificial system design F through DSM modeling. The first case depicts a system design as a DSM explicating sequential, coupled, and parallel connections. Constructing a *sequential mapping* from one element to another resuls, for instance, in the pair(A, B) or pair(A, B, C, D). The DSM hence gets a one in column A and row B. Importantly, the pair(B, A) differs from the previous pair (pair(A, B)≠pair(B, A)) and depicts the flow from B to A. Taking both pairs together, the DSM demonstrates *coupled mapping*, which is a recursive flow. The last case concerns *decoupled mapping*, where Figure 6 exemplifies E, as decoupled from A, B, C, D. In other words, E behaves independently and does not change when the other elements are involved. Next, DSM modeling comprises two systems.

[6] This thesis acknowledges that not every numerical pair between domains must have an underlying function. The wording *mapping* will contain functions and relations in a mathematical sense and is interchangeable for both.

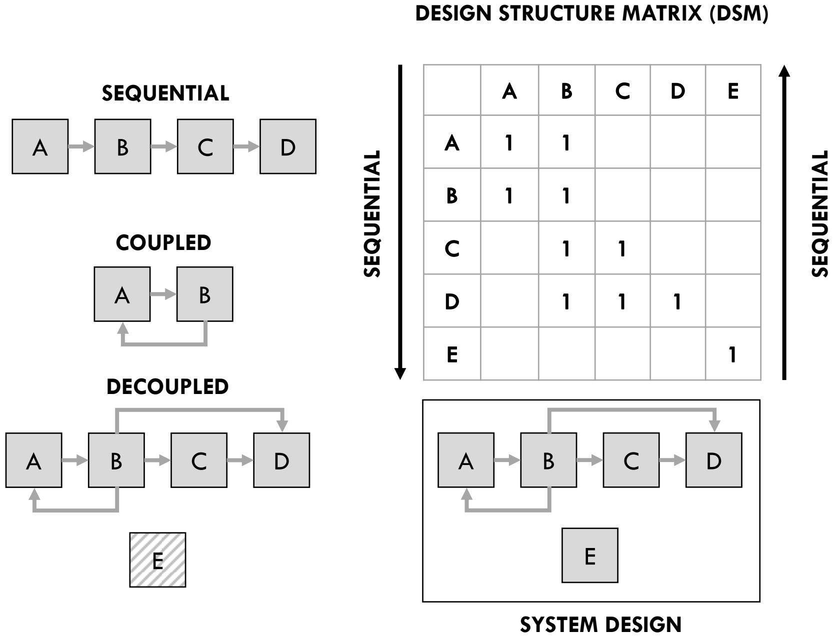
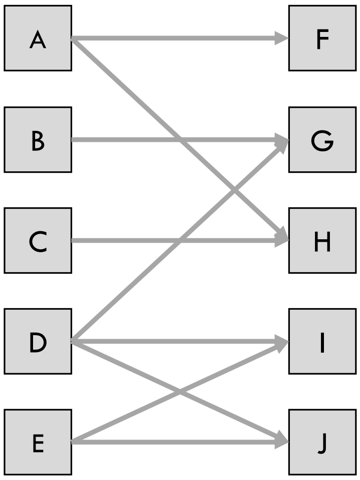


Figure 6: DSM modeling

Figure 7 presents a domain mapping matrix (DMM) that contains interconnections of system design, shown by the sets A, B, C, D, E and F, G, H, I, J. A DMM primarily maps system designs to each other and does not account for a direction in contrast to a DSM, as shown by Eppinger and Browning (2012). In other words, row elements direct to column elements and the other way around. For instance, pair(B, G) means that B is solely mapped to G, where the entry in the DMM reflects the potential design elements *A*. Taking the example into a vector notion conducts a possible function of G=$A_{G,B}$ B and unveils the suitability of $A_{G,B}$. For instance, a B of five with an $A_{G,B}$ =1 results in five G, too.

Adding this context into the DMM, with A, B, C, D, E as the input parameters and F, G, H, I, J as the output parameters, clarifies the interpretation to some degree. In the context of independent and dependent parameters, the DMM is one partial element of the hierarchical systems' design. The DMM hence reflects a system design matrix by $Y=A_{X,Y}X$, which is a mathematical vector notation of the subsystem $F(X)=Y$. In other words, the design of $A_{X,Y}$ can cover a large set of functions within a system's design *F*. Summarized, DMMs can describe systems' design *F* through inputs *X*, outputs *Y*, and a design matrix $A_{X,Y}$.



DOMAIN MAPPING MATRIX (DMM)

	F	G	H	I	J
A	1		1		
B		1			
C			1		
D		1		1	1
E				1	1

Figure 7: Building a requirement matrix through DMMs

Figure 8 describes the system $Y=F(X)$ further using two DSMs and one DMM. This assumes that X contains a fully decoupled DSM, meaning that there is no interrelation between the inputs. This parallels a realistic orthogonal design in M&S (Law, 2014b; Siebertz, van Bebber, & Hochkirchen, 2010) because complexifying systems' input is needless. By contrast, the dependent variables Y have one interrelation through the pair(Y_2, Y_1), meaning that Y_2 is based on Y_1. This is no exception because models frequently have several stages that typically requiring initial or intermediate inputs. The DMM in Figure 8 thus necessitates a numeric design.

At this point, the matrices formalize a system design; however, it is also possible to use descriptions and mappings further. Assume that Y_2 is a necessary output such as a product. When the system wants to supply one Y_2, it will trigger the first design equation of $Y_2=5X_1+ 1X_2 + 1Y_1$ and automatically the second of $Y_1 =X_1 + 2X_3$. In sum, the input must be $X_1=6$, $X_2=1$, and $X_3=2$ for receiving one $Y_2=1$. This principle underlies neoclassical consideration in production theory and strengthens the choice of DSM modeling. This is an abstract example to demonstrate the modeling applied in this thesis.

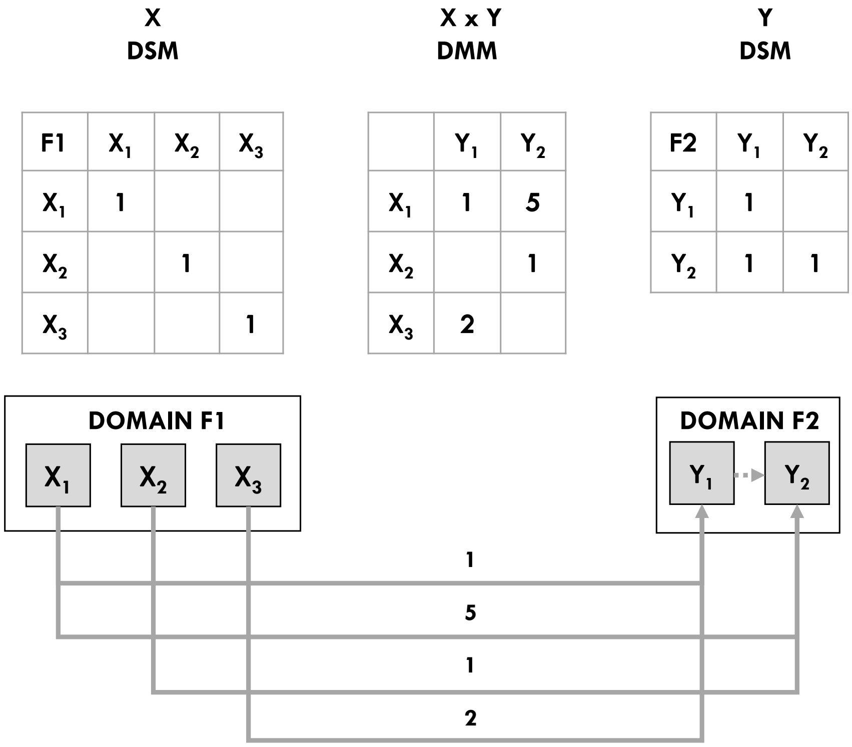


Figure 8: A system of two DSMs and one DMM

Overall, DSM modeling allows us to analyze complex networks to understand their scalability and applicability to computational procedures. The choice of DSM modeling has several advantages. First, using DSM modeling to implement conceptual models to computational models profits from parallel developments. The clustering and sequencing algorithms of DSMs and DMMs facilitate their application. Second, broad applications in research and practice support communicability (Lindemann et al., 2009; Sosa et al., 2003, 2004; Yan & Wagner, 2017; Yassine et al., 2003). Third, all matrices are visualizable, which fosters understanding to more realistic settings. To sum up, designing complex systems employing DSM modeling can understand and communicate without neglecting computational scalability and applicability.

2.2 Product program

2.2.1 Product-based planning

The progress and interplay of multiple business strategies manifest in product-based planning to define firms' product and production program, as illustrated in Figure 9 (Arend, Zhao, Song, & Im, 2017; Balakrishnan et al., 2011; Krause & Gebhardt, 2018; Robertson & Ulrich, 1998). Product-based planning starts with the identification of customers' expectations. Based on this information, firms can target specific customer segments through the development of products with suitable functionalities (Banker & Johnston, 2006; Jonas, Gebhardt, & Krause, 2012; Ulrich & Eppinger, 2012).[7] The collection of the product design characteristics for future new product development (NPD) is part of the marketing strategy (Banker & Johnston, 2006; Jonas et al., 2012; Robertson & Ulrich, 1998). Operating strategies include planning prospective technologies and processes (i.e., for capacity planning) using the NPD process design characteristics to ensure sufficient supply for expected demand. In sum, product-based planning determines product variants, families, and production lines in line with the firm's strategies.

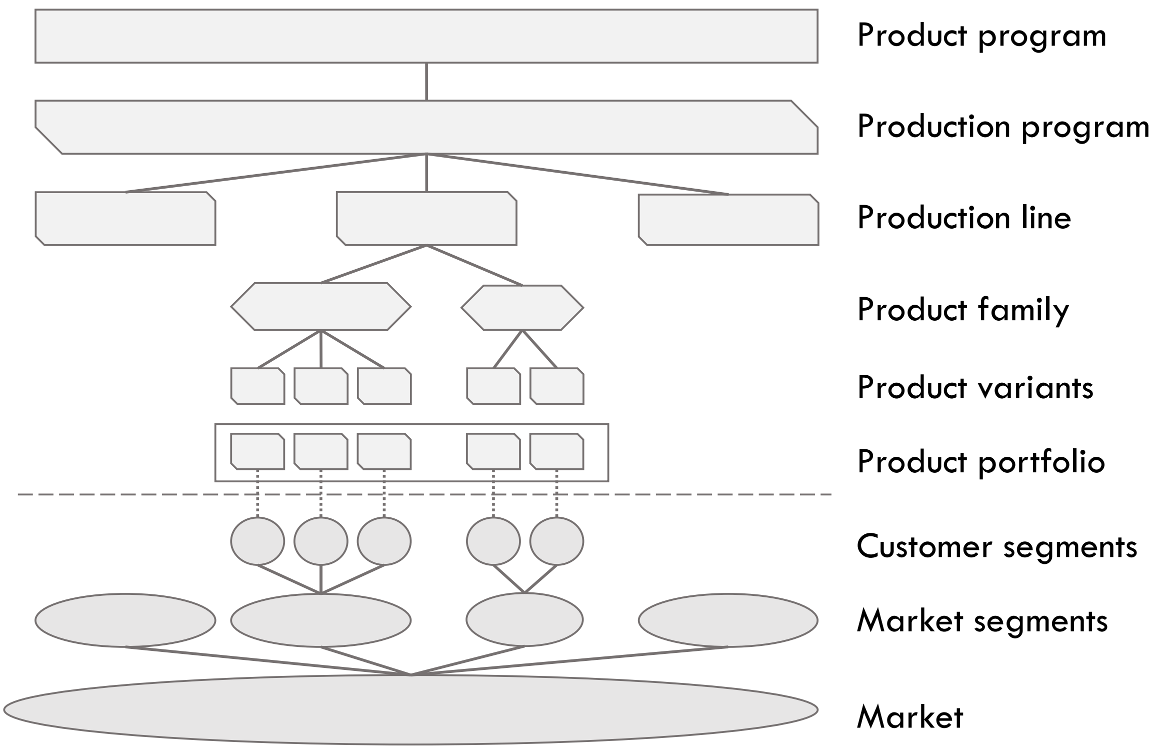


Figure 9: Product program (Krause & Gebhardt, 2018) with market extension

Marketing strategies aim to identify customers' needs to derive the functional characteristics that support design choices within NPD. The market side offers nearly unlimited design choices for product variants, and marketing can reduce this uncertainty by identifying worthwhile customer segments. This

[7] Some studies use product segments instead of customer segments (Kotler & Keller, 2015). This thesis does not see a conceptual difference and retains customer segments to accentuate the market perspective.

is known as customer targeting and is part of efficient NPD (Du, Jiao, & Tseng, 2005; Ulrich & Ellison, 1999; Xu et al., 2009). When marketing targets customer segments, NPD acquires the market information and provides production design characteristics.

Operation strategies are devoted to efficient technology and capacity planning to secure the continuous supply of every product variant given expected demand (Balachandran, Balakrishnan, & Sivaramakrishnan, 1997; Banker & Hughes, 1994; Banker, Hwang, & Mishra, 2002). The design characteristics from marketing frame the necessary production procedures. The operation strategy hence decides on the process design characteristics, which determine the properties of the production lines. The production line then requires capacity such as workers and machines to supply sufficient resources for production.[8] As a final result, the interplay of the strategies in product-based planning defines firms' future product and production program.

2.2.2 Product variety

Because markets can own a myriad of customer segments that constitute a possible range for NPD, a large product variety can result. Assuming firms have a profit maximization motivation and aim to increase the revenue of new product variants, this often prevents a reasonable break from developing more products. Specifically, having markets with many distinct customer segments provides a rich ground for many product variants. In its extreme, this results in the ideal state of "mass customization", where each customer segment has its own specific variants(Jiao & Tseng, 1999; Pine, Bart, & Boynton, 1993). This circumstance has prompted the investigation into complexity management and postponement (Abdelkafi, 2008; Blecker, Wilding, & Abdelkafi, 2006; Feitzinger & Lee, 1997; Jiao & Tseng, 1999; Ramdas, 2003). Nonetheless, this also leads to the classical trade-off between the value of product variety and costs of complexity in production (Banker & Johnston, 2006; Krause & Gebhardt, 2018; Shank & Govindarajan, 1989).

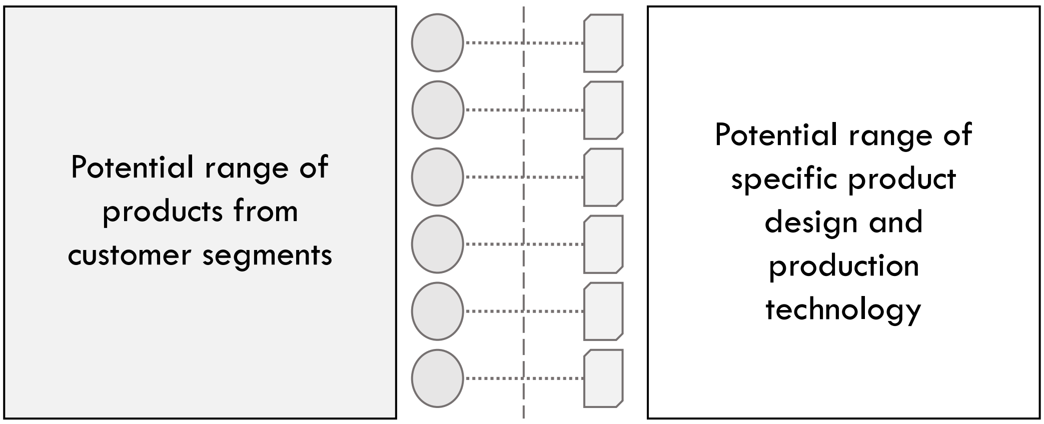


Figure 10: Market potential can cause product variety

[8] This topic is also prominent under capacity program planning in economics (Balakrishnan & Sivaramakrishnan, 2002).

Figure 10 illustrates an arbitrary market potential through various customer segments, where each can be a motivation for NPD. When firms only follow the market, sooner or later, variety in the product portfolio rises markedly (Fisher, Ramdas, & Ulrich, 1999; Henderson & Clark, 1990; Jiao & Tseng, 2000; Ramdas, 2003), thus diffusing toward production lines. Unfortunately, this internal variety tends to increase costs (Desai, Kekre, Radhakrishnan, & Srinivasan, 2001; Fisher et al., 1999; Fixson, 2007; Kekre & Srinivasan, 1990). Assuming that every customer segment is dissimilar in at least one customer need, products must have a certain degree of specificity (Schilling, 2000; Schilling & Steensma, 2001). In simple terms, it is not sensible to offer too similar products, because less specificity leads to cannibalization (Kim & Chhajed, 2000; Moorthy & Png, 1992; Raghavan Srinivasan, Ramakrishnan, & Grasman, 2005). Providing unique products to customers, by contrast, results in specific functions, components, processes, and resources (Fixson, 2007; Schilling, 2000; Simpson, 2004). This increases, for instance, the variety of components and related production efforts primarily associated with spiraling costs (Labro, 2004; Ripperda & Krause, 2017; Wouters & Stadtherr, 2018). This causal relationship is not new (Baker, Magazine, & Nuttle, 1986; Collier, 1981; Gerchak, Magazine, & Gamble, 1988; Treleven & Wacker, 1987), and research and practice are still seeking to offset specificity through, for instance, more generic product architectures.

2.2.3 Product architecture

Figure 11 demonstrates a product architecture with a functional and physical structure that maps products’ functions to components following Ulrich (1995) and Göpfert (1998). A product architecture is the ontological framework consisting of mappings between products’ specifications and physical components (Ulrich, 1995). Göpfert (1998) adds the functional and product structure that describes the internal linkages between components and functions. Of particular interest is that this framework has become a common theory in management and engineering (Eppinger & Browning, 2012; Schilling, 2000; Ulrich & Eppinger, 2012) and is decisive in questions of performance (Jiao & Tseng, 1999, 2000; Martin & Ishii, 2002). Overall, the product architecture integrates customers’ perspectives of products’ functions with the internal physical domains of firms.

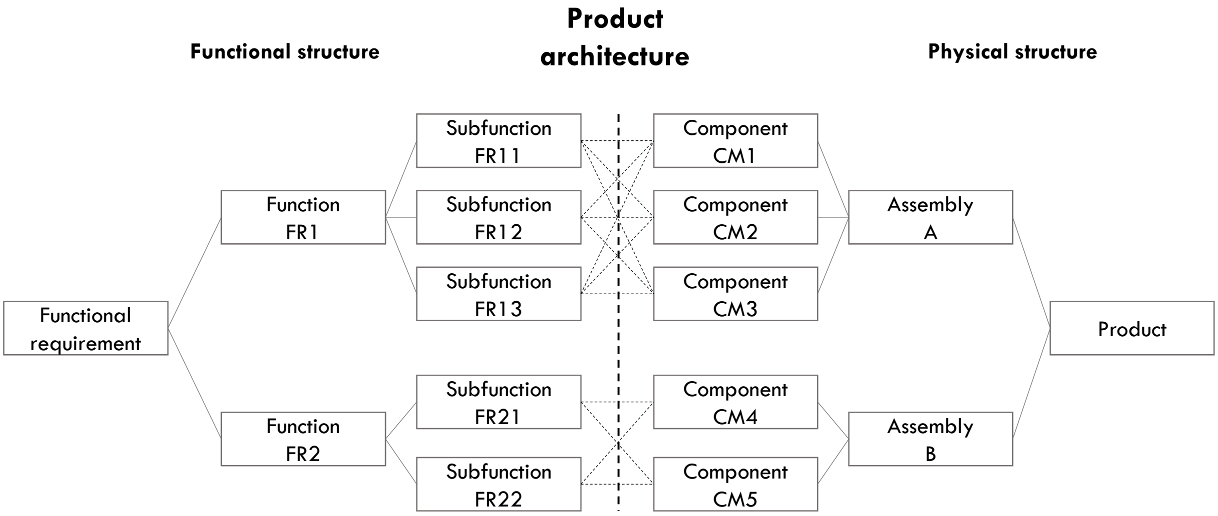


Figure 11: Product architecture with a functional and physical structure (Göpfert, 1998; Ulrich, 1995)

Products are sets of specifications, engineering metrics, attributes, or functional requirements respectively that correspond to customers' needs and components (Chan & Wu, 2002; Jiao & Tseng, 2000; Martin & Ishii, 2002; Stone & Wood, 2000).[9] Functions are, for instance, power or resistance characteristics (Fisher et al., 1999; MacDuffie, Sethuraman, & Fisher, 1996), where the physical structure includes components such as electronic boards, cases, and sensors. Under engineering design theory, functions are the communicable basis of products (Stone & Wood, 2000); moreover, components are no longer only physical elements because they can also reflect digital information and knowledge (Du, Jiao, & Tseng, 2001; Eppinger & Browning, 2012; Jiao & Tseng, 2000; Martin & Ishii, 2002).

A characteristic of product architectures is their degree of modularity and integrality (Baldwin & Clark, 2000; Fixson, 2006; Göpfert, 1998; Hölttä-Otto & de Weck, 2007; Ulrich, 1995), which highlights the number of function-sharing components.[10] Consider the product architecture in Figure 11; functions can have one or more mappings (dashed lines) to components. When functions have many connections to components, this is known as an integral product architecture. For instance, integrality means more couplings to components, where a laptop is preferably integral in contrast to a more classical computer. A classical computer tower is probably more of a modular architecture because functions have fewer mappings to components. For instance, the hard disk for saving data may be easier to decompose because it has fewer connections to other components. Overall, the product architecture is central to improvements and made decisions about design (Fixson, 2005; Mikkola, 2007; Mikkola & Gassmann, 2003; Suh, 1995).

[9] The engineering design and economic communities share the same understanding of a "product" (Fisher et al., 1999; Martin & Ishii, 2002), seeing it as a bundle of specifications, engineering parameters, and products' attributes. The terminology of this thesis is functional requirements, which is interchangeable.

[10] The interpretation of modularity differs slightly in the context of *modular design* and *modular architecture*. While design interpretations concern modules as objects for offering product variety with fewer elements, the architecture interpretation sees a modular as a characteristic rather associated with being differentiated or encased in a function. In other words, there modularity means less function-sharing components.

2.3 Cost accounting systems

2.3.1 Product costing systems

Product costs carry aggregate monetary information on particular products' resource consumption that influences and facilitates many decisions such as performance, pricing, capacity, and inventory evaluation (Balakrishnan et al., 2012a; Demski, 2008; Labro, 2019; Labro & Dierynck, 2018). The cost measurement process is located in cost accounting systems or costing systems (Drury, 2015; Horngren et al., 2014). Grounded in resource consumption and prices, costing systems first aggregate costs to resource cost pools such as aggregated labor costs, employees' salaries, summed material costs, and depreciation costs. Depending on information availability, the system can either directly trace costs to their origin or carry out additional calculations to allocate the remaining indirect costs.[11] In any case, costing systems seek to accurately measure and allocate the resource costs to their cost objects.

Regardless of the cost object, costing systems have a typical design. Figure 19 presents the typical two-stage allocation process. More stages are also possible when, for instance, considering service allocations, but this is not necessarily conceptually different (Balakrishnan et al., 2012a). An often neglected step "zero" is the construction of direct and indirect resource cost pools by assigning expenses to the respective accounts in information systems. The first stage hence groups indirect resource cost pools to overhead cost pools. Direct cost pools are directly traced to their causing object. The grouping of indirect costs can take several forms with different rules. Whereas some pools pertain to responsibility grouping rules, others are functional or activity-based (Balakrishnan et al., 2011; Lanen, Anderson, & Maher, 2013). Lastly, the second stage of costing systems allocates overhead cost pools to cost objects by employing a cost driver (Babad & Balachandran, 1993; Homburg, 2001).[12] There, each cost object receives its respective overhead costs and provides information on resource consumption.

In greater detail, the first stage (I) concerns the aggregation and differentiation of costs from the priced resource consumption. The vast amount of individual resource consumption in firms is typically gathered by information systems or manually entered by employees. However, and rarely explicitly mentioned, costing systems aggregate these individual resource costs, too. As a result, similar costs are grouped into resource cost pools, such as material, labor, administrative, and development costs. Depending on information availability, costing systems thus differentiate costs into either direct costs or overheads.

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[11] Indirect costs are separable into general administrative expenses and overheads (Horngren et al., 2014). Overheads are more clearly allocable to projects, whereas general administrative indirect expenses are more related to general activities not tracable to projects. For simplicity reasons, this thesis uses overheads, overhead costs, or indirect costs interchangeably to represent all these kinds of indirect costs.

[12] Several cost system designs such as resource cost accounting and time-driven ABC use the resource cost driver directly. A relevant study of this topic is Hoozée and Hansen (2018).

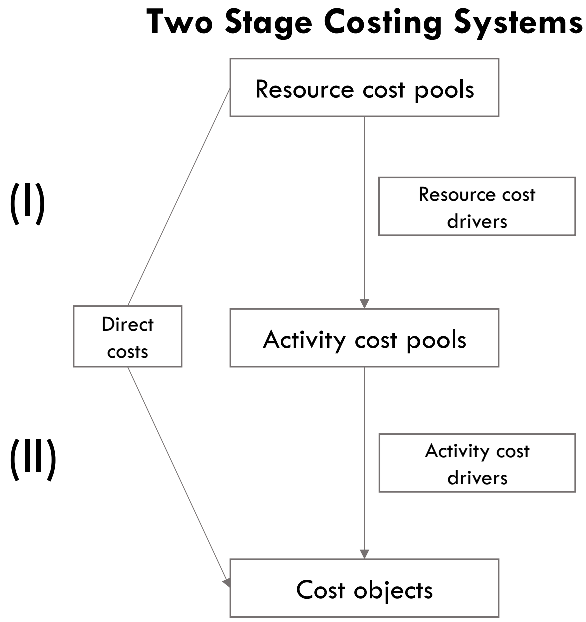

Figure 12 Two-Stage Cost Measurement System

The second stage (II) concentrates on cost pool building and overhead allocation. Cost pools cluster indirect resources using systematic rules and allocate them to their cause. Complex costing, for example, groups overheads to their underlying processes in overhead cost pools, whereas simple ones tend to use the organizational structure. Ideally, the resulting activity measures (i.e., hours or units) accurately mirror the resource consumption to allow costs to be correctly allocated (Noreen, 1991). As a result, products receive their consumed resource costs and provide accurate product cost information.

2.3.2 Cost system design choices

While the typical cost measurement process is known, the design choices of costing systems under the consideration of firm characteristics remain opaque. Cost accounting textbooks highlight the TVC and full ABC systems as the dominant types of cost system designs (Drury, 2015; Horngren et al., 2014; Lanen et al., 2013). The simplest one is TVC, whereas the most complex is an ABC system.[13] On the question of appropriateness and performance, research has continuously provided descriptive evidence but not found a clear pattern (Al-Omiri & Drury, 2007; Drury & Tayles, 1994, 2005; Ittner, Lanen, & Larcker, 2002; Krumwiede & Charles, 2014; Lukka & Granlund, 1996; Malmi, 1999; Schoute, 2009, 2011). Despite their higher accuracy, surprisingly, complex ABC systems have not thus far diffused in practice. Moreover, research has not comprehensively disentangled the focal drivers or reasons for firms applying complex costing systems (Abernethy et al., 2001; Schoute, 2009, 2011). Overall, although

[13] The most frequently used simple cost accounting system is TVC, which reflects the usage of one overhead cost pool and one cost driver (Al-Omiri & Drury, 2007; Drury & Tayles, 2005). The cost driver is simple such as production output and labor hours. The opposite is the full ABC system, which disentangles and identifies the activity measures of all activities. In doing so, each activity is allocated the right costs, leading to “perfect” product costs.

ABC advocates claim that it is superior, more complex costing systems have not reached gold standard status.

There is still a certain ambiguity about what a complex costing system is, with empirical research providing some of the distinctive characteristics of simple and complex costing systems. The first antecedent is the number of cost pools and cost drivers. Similarly, the rules, designs, and heuristics of cost pool building as well as cost driver selection are significant, too. Second, cost driver type is presumed to be another antecedent because ABC systems employ all kinds of activity measures as cost drivers (Babad & Balachandran, 1993; Park & Simpson, 2008). Here, cost structure theory is particularly relevant (Anderson & Sedatole, 2013; Cooper, 1990). Another antecedent may be the number of stages in cost accounting systems because the service allocation stage may increase and enhance cost information (Balakrishnan et al., 2012a). All these characteristics form the definition of a complex costing system visualized in Figure 13.

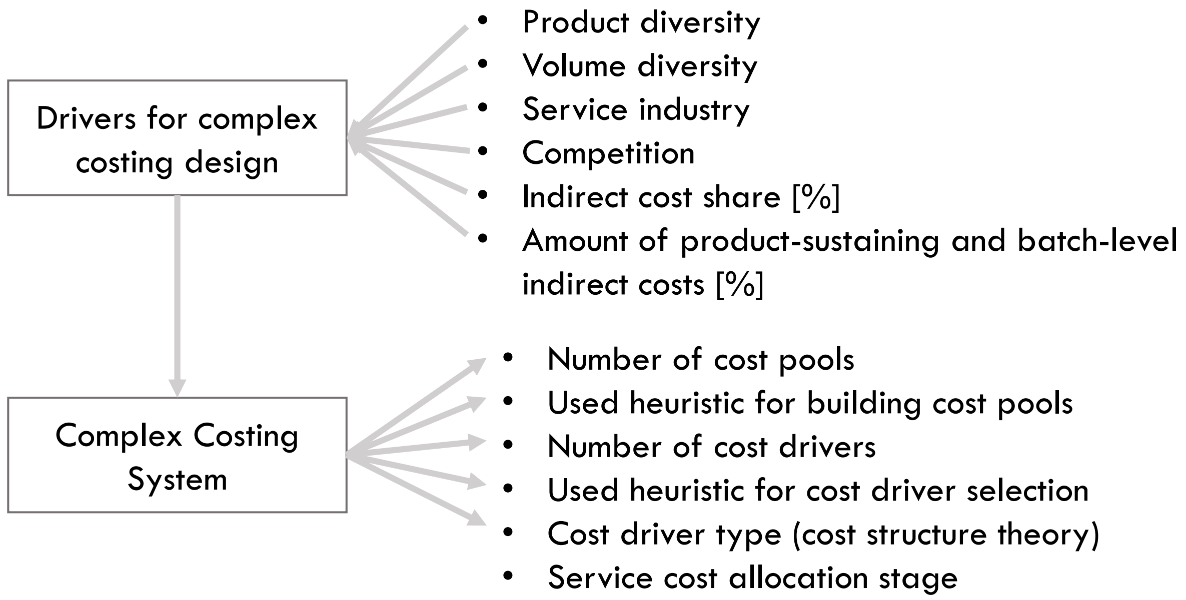

Figure 13: Conceptual summary of the drivers for adopting and rejecting complex costing systems

Although the properties of complex costing systems are distinctive, the reasons for adopting them remain unclear (Banker, Bardhan, & Chen, 2008; Cagwin & Bouwman, 2002; Gosselin, 1997; Schoute, 2009). The adoption of complex costing systems has been found to be necessary to have cost advantages (Shank & Govindarajan, 1993); however, firms have often abandoned such complexity (Anderson, Hesford, & Young, 2002; Kaplan & Anderson, 2003). Why firms adopt or reject a complex costing system can be understood by observing potential antecedents such as product diversity, competition, and industry (Al-Omiri & Drury, 2007; Drury & Tayles, 1994, 2005; Schoute, 2009, 2011). Unfortunately, except for competition, size, and service industry level, variables such as product diversity and indirect cost share provide inconclusive findings. Figure 13 also shows the presumed antecedents for cost system design choices.

The theory-building study of Abernethy et al. (2001) qualitatively examines whether product diversity and product- and batch-level costs are an indicator of adopting complex costing systems. They argue that cost structures with product-level and batch-level activities highlight the need for complex costing systems because TVC does not incorporate more driver types.[14] Specifically, when there are fewer non-unit-level activities, ABC's utility is likely to be less. Some empirical research has corroborated this relationship (e.g., Fisher et al., 1999; Malmi, 1999); however, surprisingly, not every study has found support for it (e.g. Cagwin & Bouwman, 2002). More recently, Abernethy et al. (2001), supported by Drury and Tayles (2005) and Schoute (2011), find that it has a significant impact, whereas Al-Omiri and Drury (2007) offer the contrary finding.

Another strand of the literature has searched for evidence that ABC systems improve performance (Banker et al., 2008; Cagwin & Bouwman, 2002; Ittner et al., 2002; Krumwiede & Charles, 2014) and, again, inconclusive findings have appeared. Less accurate cost information is presumed to lead to errors in decision-making, especially when using simple TVC systems. Following recommendations (Cooper & Kaplan, 1991, 1992, 1998a), ABC systems overcome this limitation by providing more accurate cost information and may be associated with greater performance. In particular, ABC has a positive impact in cost-sensitive environments (Krumwiede & Charles, 2014). However, whether complex costing systems perform better remains doubtful.

In summary, discussion on the adoption reasons and performance benefits of applying complex costing systems is ongoing. Researchers and practitioners often assume that complex costing systems outperform simple costing systems. However, there is no convincing empirical or practical evidence of the antecedents of adoption and profitability. Moreover, there is still discussion on whether the accuracy of cost data can improve decision-making (Anand et al., 2017; Labro, 2019; Merchant & Shields, 1993).

3. State-of-the-art

3.1 Modern cost measurement

3.1.1 Revisiting cost accounting

This section departs from the basic understanding presented in Section 2 and revisits cost accounting research. It does not try to provide a systematic review of recent cost accounting issues but instead aims to offer a comprehensive and condensed introduction of the essential concepts and developments in costing system research to position the contributions of this thesis among the literature.

[14] Following Al-Omiri and Drury (2007) and Cooper and Kaplan (1998a), product diversity is a construct that encompasses several elements such as process layout, product design characteristics, underlying production volume, and support activities. A broader discussion about product diversity can be found in Trattner, Hvam, Forza, and Herbert-Hansen (2019).

A starting point for modern cost accounting was triggered by Miller and Vollmann (1985), who were among the first to indicate that costs are not strictly proportional to production volume. Nowadays, this is an intuitive assumption; however, in the past, disproportionate costs and production volume conflicted with neoclassical production theory (and still does) (Christensen & Demski, 1995; Cobb & Douglas, 1928; Shepard, 2015). For instance, Shank and Govindarajan (1988) conclude from this evidence that this classical costing approach is outdated compared with "transaction-based" systems. As a result, early research activities concentrated on cost drivers and problems when not considering transaction-related costs.

There has been much cost driver research (Babad & Balachandran, 1993; Banker & Johnston, 1993; Banker & Potter, 1993; Datar, Kekre, Mukhopadhyay, & Srinivasan, 1993; Foster & Gupta, 1990), with Banker and Johnston (2006) offering a comprehensive review. These studies find that other drivers besides volume explain variance in the costs well. Interestingly, although the explained variances differ between studies and cost drivers chosen, this strand has shown that transaction-related activities are associated with a noticeable share of cost in firms.

Paralleling the practice-orientated literature, Cooper (1989); Cooper and Kaplan (1987) state that transaction costing is necessary to stay competitive. Although there is no official inception of ABC in the literature (Gosselin, 2006; Jones & Dugdale, 2002), the inclusion of non-unit cost drivers in costing may have reflected the start (Cooper, 1990). Based on the assumption that transactions affect resource consumption, the first papers claimed that ABC systems were superior to the TVC system (Cooper & Kaplan, 1991).

Simplifying the cost driver selection in ABC systems, likely for implementation issues, led to the development of the ABC hierarchy, a cost structure theory that categorizes activity measures into the underlying resource consumption (Cooper, 1990; Cooper & Kaplan, 1991). Although the empirical literature has found evidence for the explanatory power of non-unit cost drivers, evidence for the cost structure theory of ABC is inconclusive (e.g. Ittner, Larcker, & Randall, 1997). Indeed, whether the ABC hierarchy is better than the classical categorization of fixed and variable cost types remains unclear (Anderson & Sedatole, 2013).

Noreen (1991) analytically defines cases when ABC systems provide marginal product costs and started discusses accuracy further.[15] In his analysis, he states that ABC systems only provide marginal costs under three assumptions. First, non-linear activities such as a Cobb–Douglas function with increasing or decreasing returns to scale distort product costs because the "linear" cost driver cannot proxy for the underlying "non-linear" resource consumption. Second, joint processes cannot be acknowledged, while activities must be differentiable to specific products and drivers. Third, total costs

[15] Marginal costs reflect the "true" costs of producing one more unit in microeconomics. However, when propositions of the ABC framework are violated, this will not hold. For example, deviations from linearity prevents marginal costs (Christensen & Demski, 2003).

must be dividable into cost pools that have at least one activity. If any assumption does not hold, the ABC system will not lead to marginal product costs.

Gupta (1993) was one of the first empirical studies of cost system performance in two firms. He compares the relative accuracy of simple and complex costing systems and finds differences, particularly distortions in product cost measures. In addition, both the firms investigated have many activities, and this prevented a full ABC system. Hwang et al. (1993) capture the full effect of heterogeneity in an analytical study with a numerical simulation. Their study explores the diversity of products' production technology, product mix, and missing input costs from aggregation. All three factors interact positively in their study and drive the product cost bias. A significant finding of their study is that heterogeneity in products' production technology, meaning that each product has different consumption and activities, is the main origin of product cost errors.

Babad and Balachandran (1993) contribute to this discussion by disentangling the optimal cost driver choice in several scenarios. In their study, they conduct a narrow model to demonstrate that an error-free aggregation of several cost drivers is possible when there is a full positive correlation between them. Additionally, any deviations from those distort the product cost measurement. Besides, they introduce a combination of cost drivers, finding that an indexed cost driver leads to a feasible approach and thus more accurate estimates. In this line, Homburg (2001) provides an analytical model of cost driver selection and confirms the relevance of indexed cost drivers.

A milestone in cost accounting theory is the analytical study of Datar and Gupta (1994), who conceptually and analytically develop a typology of error causes in costing systems. They show that errors under limited information are attributable to aggregation, specification, and measurement errors. These three types are the current ontology for error causes. First, aggregation errors arise from the aggregation of heterogeneous consumption (i.e., building a cost pool with dissimilar activities such as from administration and marketing). Second, specification errors reflect a wrong decision in terms of cost driver choice (i.e., using labor hours instead of machine hours for a machine activity cost pool). Finally, (random) measurement errors arise from uncontrollable reasons such as typing errors and manipulation in the information system (Weber, 2005).[16] They also find that increasing cost pools is likely to increase measurement errors and thus worsen the accuracy of cost measurement. This effect was later substantiated by Cardinaels and Labro (2008). Nonetheless, Datar and Gupta (1994) question the unassessed rule that complex costing systems, particularly ABC-based systems, always lead to fewer errors.

The empirical study of Hwang and Kirby (1994) examines the consequences of a single allocation driver in an empirical setting (i.e., hospital reimbursement). They first provide the detailed attributes of cost objects (i.e., patients) and enriched information compared with implemented costing systems. Each patient is classified into private/public insurers as well as young/old patients. These attributes are used

[16] Datar and Gupta (1994) use the term "measurement error" to describe imprecision. This thesis sees a measurement error as a general error and explicates uncontrollable errors as random measurement errors.

to update the existent cost allocation base with patients' days. This update substantiates the classical cross-subsidization of TVC systems because they find that private- and public-insured patients are cross-subsidized. Specifically, private patients are undercosted, while public ones are overcosted due to younger private patients released within fewer days in contrast to older and publicly insured patients who stayed longer.

Noreen and Soderstrom (1994, 1997) also assess linearity in ABC systems in the area of hospitals. Their hospitality case shows that the linearity assumption of ABC systems is not substantiated. Noreen and Soderstrom (1994) primarily assume linearity in activity cost drivers. This leads to the proposition that the average cost driver must be constant across all sums of activity measures. However, they do not find linearity, because the cost driver shrinks when activity measures increase. This observation confirms the increasing returns to scale of an activity driver, which cannot yet be accounted for in ABC systems. The subsequent study of Noreen and Soderstrom (1997) demonstrates that increasing returns to scale leads to undercosting (overcosting) when a product consumes less (more) of an activity. Hence, ABC has lost much of its superiority of being error-free.

Given the empirical support that activity cost drivers do not behave linearly, Christensen and Demski (1997) analytically address the question of how they affect cost information. They show that non-linearity has substantial implications on the reported outputs from ABC systems and that managers should be prudent. Additionally, they find that not all product costs profit from complex costing systems. For instance, in some cases, better costing systems measure individual product costs more inaccurately.

Christensen and Demski (2003) examine ABC and TVC under non-linearity. They provide an analytical case in which a complex costing system does not necessarily lead to better product cost estimates than a TVC system. Even modest deviations from linearity (i.e., diseconomies of scale or simple bottlenecks) quickly shift most ABC systems to worse performance than simple ones. They further re-emphasize the still unanswered question of whether complex costing systems always lead to more accurate product costs.

The simulation study of Labro and Vanhoucke (2007) points out that any refinements in costing systems lead to less product cost errors on average despite three exceptions. Before this study, Datar and Gupta (1994) claimed that refinements do not strictly improve accuracy. Their simulation study thus sharpens the discussion and shows that refinements toward more complex costing systems improve accuracy under three exceptions.[17] They also analyze the interactions among aggregation, specification, and aggregation errors and suggest cases of the offsetting effects of aggregation and measurement errors. Additionally, their data show cross-subsidization behavior in ABC systems that slightly undercosts cheap product costs and overcosts expensive ones. The most remarkable result is that the second stage

[17] This study identified three exceptions of decreasing accuracy despite refinements by negative interaction effects. First, there is an offsetting between aggregation errors in stage II and measurement errors in the stage I when there is a measurement error ≥50%. Second, there is offsetting within II stage under high aggregation error ≥70% and low measurement error ≤20%. Third, a similar effect at the I stage under very high measurement error =90% and aggregation error > 80%.

of costing systems is decisive in reducing product cost errors, which provides strong practical guidance for designing cost systems.

Subsequently, Labro and Vanhoucke (2008) explore the implications of diversity in the resource consumption of products in terms of sensitivity to errors. Until their study, a ‘diversity rule’ of thumb existed (Cooper & Kaplan, 1988; Horngren et al., 2014). This rule states that improving costing systems benefits product costs most when a firm has vast diversity. The study confirms that diversity is an indicator of improvements in product costing. However, there are also exceptions to this rule. For instance, it seems that less diversity in cost driver distribution over cost pools helps raise robustness to measurement and specification errors. However, products with fewer driver links to processes are sensitive to aggregation, measurement, and specification errors. Therefore, refinements in these drivers increase accuracy. In summary, Labro and Vanhoucke (2008) build a comprehensive picture of diversity in resource consumption among cost error causes.

Balakrishnan et al. (2011) compare the design choices of costing systems and highlight that less information does not inevitably reduce the effectiveness of product costing. Their simulation model surrogates numerous production environments with complex ABC systems and illustrates the advantages and disadvantages of cost pool and cost driver design heuristics. Striking from their data is that even less precise estimates of correlations between resources are enough to form accurate activity cost pools. To sum up, this study provides strong practical implications to define cost system designs.

Hoozée, Vermeire, and Bruggeman (2012) use numerical explorations to investigate the effect of additional time driver terms as well as measurement errors in time drivers on accuracy. This study adopts time-driven ABC (TDABC), which has gained significance due to its lesser information demand for implementing complex costing systems (Balakrishnan et al., 2012a; Balakrishnan, Labro, & Sivaramakrishnan, 2012b). By drawing on the concept of this study, it is observable that the largest time drivers are the most relevant for explaining the costs likely to cover smaller time drivers. To be concise, they show that large time drivers are an appropriate choice as an allocation base.

The latest strand of costing studies has moved to dynamic decision settings, where Anand et al. (2017) are the first in this line. Instead of highlighting errors in costing systems, they explain how erroneous cost information distorts a subsequent product elimination decision. As expected, products with negative contribution margins are eliminated, and many scenarios end up with a non-optimal equilibrium and thus a profit loss. A similar study also investigating decisions on cost information using pricing and capacity errors is Homburg, Nasev, and Plank (2017). They show that more accurate cost information from complex costing systems has fewer profit advantages as expected. In sum, they emphasize that cost allocation errors in pricing decisions are less significant.

Another recent costing study, namely that of Hoozée and Hansen (2018), formally disentangles the difference between classical ABC and TDABC by describing activity–resource mapping in greater detail. Mapping activities with resources influences cost system design choice: where TDABC has a one-to-one, classical ABC has a one-to-many. They conclude that TDABC has a comparative advantage over ABC referring to this mapping. Nonetheless, it is worse than classical ABC when activities are more traceable. Finally, Anand, Balakrishnan, and Labro (2019) consolidate previous simulation studies using a general framework. They do not primarily summarize the research findings but rather formalize previous simulation studies. Therefore, this sets a path for further studies f numerical cost accounting.

Overall, cost accounting research has begun to explain error causes by considering diversity in production environments under less available information. The most prominent research method for costs remains analytical with increasing numerical explorations. Rules of thumb have been proposed such as the importance of the second stage in terms of errors and that all refinements of costing systems tend to reduce product cost errors. Diverse production technology needs more complex costing systems to provide accurate cost information. Drivers such as random measurement errors and non-linearity additionally question the superiority of complex costing systems. However, simple costing has also failed to evolve. The use of TDABC provides a more straightforward implementation instead of greater accuracy. Overall, although cost accounting has accumulated many findings, it still offers vague guidance on several questions. For instance, when should complex or simple cost designs be implemented? How vital is accurate cost information on average and to what degree are errors allowed? Finally, this short review emphasizes costing as a relevant and suitable field of management accounting because many topics are still uncharted (Labro, 2019; Labro & Dierynck, 2018).

3.1.2 Product cost errors

Measuring complex unobservable phenomena with a simple measurement system may cause errors. Complex phenomena in natural science are difficult to measure, where nature scientists develop highly sophisticated instruments involving large measurement efforts and implementation costs to achieve high levels of accuracy (Abbott & et al., 2016). By contrast, firms see little value in perfect product costs even though the transparency and accuracy of such information could enhance their decisions in many ways (Banker & Datar, 1989; Bol, Kramer, & Maas, 2016; Chapman & Kihn, 2009; Nelson, Todd, & Wixom, 2005). Therefore, a balance between sufficient product cost accuracy and errors from noisy product costs (Cooper & Kaplan, 1998b) is still accepted.

Describing product cost measurement in firms starts with explaining the production technology and its set of production functions p_f. From a mathematical perspective, the general transformation process pertains to a number of production functions p_f that relate to finite set of goods (Christensen & Hemmer, 2006; Fandel, 2005, p. 35f.; Shepard, 2015, p. 13ff.). The basic description of one function p_f contains a set of minimum input requirements λ resulting in a minimum output y. In simple words, the transformation uses a certain set of inputs and transforms it into one output resulting in $y = p_f(\lambda)$.

In addition to the input-output relation, other characteristics such as substitution, intensity, and linearity are prominent.[18] Cobb–Douglas production functions do not assume fixed input proportions λ and allow for substituting inputs (Cobb & Douglas, 1928). Substitution for a bike, for example, means that it is possible to use two wheels more instead of one saddle. Such functions are mainly applied in aggregated models because they can demonstrate the extent to which capital can replace labor (i.e., buying a machine instead labor crafting). The most applied in production theory is the Leontief function, which has fixed input requirements λ that are not substitutable between each other. In this function, the bike absolutely needs two wheels and one saddle. Overall, production functions are abstract transformation functions that consume sets of input resource requirements λ to supply the requested output y.

Extending the example, imagine a bike manufacturer that receives demand for q bikes, which prompts the production functions to supply y in the quantity of q. Assume that manufacturing a bike needs the following process with minimum input requirements $\boldsymbol{\lambda}$ = {two wheels λ_1, one frame λ_2, one saddle λ_3, and one hour of a worker λ_3}. To calculate the necessary inputs, the bike results in the Leontief production function of $y = p_f(2,1,1,1) = p_f(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$. Demand for five bikes hence proportionally increases the minimum input resource requirements by five to $5y = f(2{\cdot}5, 1{\cdot}5, 1{\cdot}5, 1{\cdot}5) = p_f(q\lambda_1, q\lambda_2, q\lambda_3,$

[18] There are several well-known production functions in production theory. Most belong to the functional typology of the "constant elasticity of substitution" (Fandel, 2005). In this family, functions such as Gutenberg (Albach, 1980) and Cobb–Douglas have a strong mathematical description.

$q\lambda_4$). The multiplication results in the *total (input) resource requirement x or RCU* ($RCU = \lambda q$) $5y = f(10,5,5,5)$.[19]

At this point, cost theory includes production functions, as it multiplies total resource requirements *RCU* by their corresponding input prices ρ. Taking the bike process again, let us assume that one wheel has a price of 10€, frame 50€, seat 30€, and one working hour costs 50€. Next, the production function becomes a cost function resulting in 150€ per bike $c_f(2{\cdot}10,1{\cdot}50,1{\cdot}30,1{\cdot}50) = 20+50+30+50 = 150$€. Adding the demand of five again, the cost function increases to 750€.

This single product example is intuitive; however, it becomes more interesting when adding another bike into the production environment. Now, imagine two bikes, where the previous bike is the "simple bike" and the new one is a "complex bike". Both bikes entail the same production function but have different input requirements. For simplicity, working on the complex bike needs three hours instead of one. Knowing the input requirements and prices results in the following cost function: $c_f(2{\cdot}10,1{\cdot}50,1{\cdot}30,3{\cdot}50) = 250$€. As a result, the complex bike costs 250€ PCb_2 and the simple one costs 150€ PCb_1.

Figure 14 shows the bike example in a matrix notation – still under our full information example. The first matrix maps both products (P1, P2) to their minimum resource requirements λ. This is frequently called the resource consumption matrix. Assuming demand q for both products of one, the minimum resource input is the total resource input ($x = \lambda q = RCU$). The sum of both products yields the total sum of unit for a resource $\boldsymbol{TRU}=\{TRU_1 = 4, TRU_2 = 2, TRU_1 = 2, TRU_2 = 4\}$. Under the same prices as before, this thesis weights the production of the two bikes by the costs, resulting in an economic snapshot. Under full information, there is no cost measurement problem because all costs are directly traceable to their causes, as shown in the right matrix. Multiplying each resource input *RCU* by its price ρ and summing results in the total resource costs $\boldsymbol{RCC}=\{RCC_1 = 40, RCC_2 = 100, RCC_3 = 60, RCC_4 = 200\}$ for each input resource *RC*. Unfortunately, this is still an infeasible setting.

[19] There is inconsistency between the abbreviations used for total resource requirements. Whereas Anand et al. (2019) use *RCU*, analytical studies as Christensen and Demski (1995, 1997, 2003) use *x*. Both are interchangeable; however, this thesis uses *RCU*.

Production environment

	RC_1	RC_2	RC_3	RC_4
P1	2	1	1	1
P2	2	1	1	3

'True' Cost Example

	RC_1	RC_2	RC_3	RC_4	∑ PCb
P1	20	50	30	50	150
P2	20	50	30	150	250
∑RCC	40	100	60	200	

Cost measurement systems

(a)

	$CP_{1,2,3,4}$
	400
	RC_1
P1	2
P2	2

(b)

	$CP_{1,3}$	$CP_{2,4}$
	100	300
	RC_1	RC_4
P1	2	1
P2	2	3

(c)

	$CP_{1,4}$	RCC_2	RCC_3
	240	100	60
	RC_1	RC_2	RC_3
P1	2	1	1
P2	2	1	1

(d)

	RCC_1	RCC_2	RCC_3	RCC_4
	40	100	60	200
	RC_1	RC_2	RC_3	RC_4
P1	2	1	1	1
P2	2	1	1	3

Simple costing system → Complex costing system

Figure 14: Cost measurement example

The balanced strategy results in limited information, and this interacts with the diversity of production to dilute the "true" cost setting. Relaxing the assumption of full information leads to the classical cost allocation problem (Zimmerman, 1979). Figure 14 shows the bike environment when assembling a simple (P1) and a complex bike (P2) in a benchmark or "true" scenario. The opposite scenario concerns no information, meaning that all costs are indirect. This assumption entails several potential measurement scenarios, and this thesis selects four (*a*,*b*,*c*,*d*) to provide example cases of product cost errors.

First, under the simplest costing system (a), the system has only one consumption pattern. This consumption is thus used as an allocation base to allocate all costs from a single cost pool $CP_{1,2,3,4}$ to both products ($CP_{1,2,3,4}$ = $\boldsymbol{RCC}$). The allocation base does not reflect individual products' resource usage and this results in product cost distortion (PCh_1 = 200€ vs. PCb_1 = 150€ and PCh_2 = 200€ vs. PCb_2 = 250€). Case (b) contains two allocation bases and cost pools; surprisingly, this measurement system can provide "true" product costs with fewer measurement efforts than complex costing systems (d) (PCh_1 = PCb_1 = 150€ and PCh_2 = PCb_2 = 250€). Here, the allocation base reflects the average resource consumption of products with fewer allocation bases in a homogeneous grouping (Babad & Balachandran, 1993). Scenario (c) distorts the product costs again because the costing system neither clusters homogeneous resources nor applies the right allocation bases. The last case (d) fully resolves the production environment and is the "true" costing scenario. Table 1 completes the example and shows the errors in cost information in percentage terms. These cases conceptually illustrate that product cost errors arise from limited information given the heterogeneity in the production environment in accordance with Babad and Balachandran (1993); Hwang et al. (1993).

Table 1: Percentage errors in the shown costing system

	Percentage error between the "true" and measured product costs [%]			
Product	Case (a) Simple costing	Case (b)	Case (c)	Case (d) Complex costing
Simple bike P1	+33.33% (overcosted)	0% (no error)	+33.33% (overcosted)	0% (no error)
Complex bike P2	-20% (undercosted)	0% (no error)	-20% (undercosted)	0% (no error)

While information limitations are less measurable (Dopuch, 1993), measures of heterogeneity are common among the engineering and management communities (Gupta, 1993; Kota, Sethuraman, & Miller, 2000; Mikkola & Gassmann, 2003).[20] Figure 15 introduces the intra- and inter-heterogeneity measures inspired by Gupta (1993). Intra-heterogeneity (*INTRA*) focuses on products' production technology in terms of relative variances in average consumption. The more dissimilar usages are, the more substantial *INTRA* is. This calculation helps identify products with variance in usage. Measuring intra- and inter-heterogeneity illustrates the diversity of production from two angles. P1 (*INTRA*=0.25) is more intra-heterogenous than P2 (*INTRA*=0.15). Although the distances between consumption are equal, the average consumption of P1 is less than that of P2, leading to a large diversity in the first resource RC_1.

Products' inter-heterogeneity evaluates products' position in the product portfolio or family by measuring its dissimilarity from other products. Assessing *INTER* shows no disparities between the products (both *INTER=0.25*). This result is explainable because processes' average consumption is similar. For example, RC_4 has an average of two, where P1 and P2 only deviate by one. Thus, both products have the same distance to the average of production and do not necessarily have a different product mix. Equation (1) demonstrates the calculation procedure used to measure the degree of product dissimilarity.

[20] Engineering and management communities measure complexity, diversity, and heterogeneity in various contexts. Engineering fields tend to measure homogeneity, called commonality, whereas management fields observe heterogeneity.

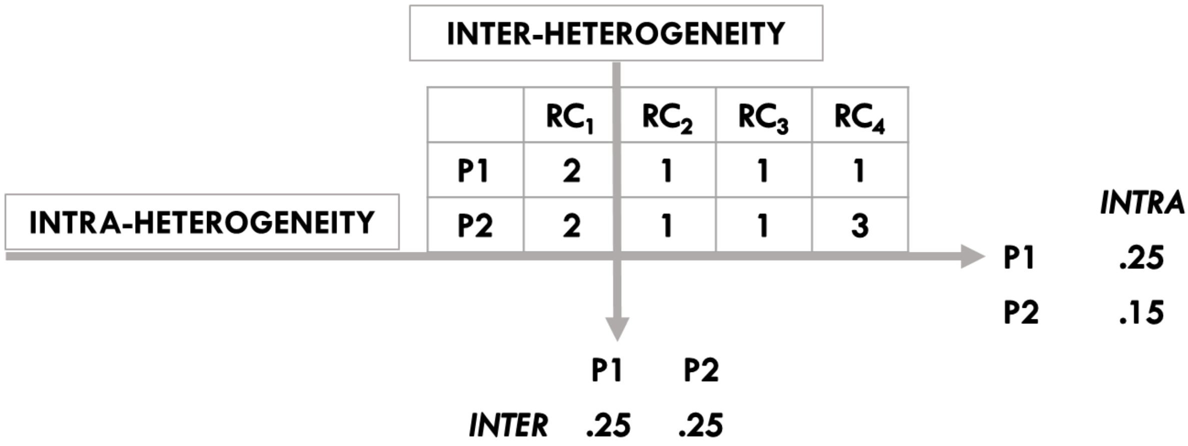

Figure 15: Example of intra- and inter-heterogeneity

$$INTRA = \sum_{n=1}^{N} \left(\frac{R_{nv} - mean(R_{Nv})}{mean(R_{Nv})} \right)^2 \; ; \quad INTER = \sum_{v=1}^{V} \left(\frac{R_{nv} - mean(\sum R_{nV})}{mean(R_{nV})} \right)^2 \qquad \textbf{(1)}$$

This section sets out the principles of product cost errors, which are grounded on the interplay between *limited information* and *heterogeneity in production technology*. In detail, hidden consumption due to limited information obscures the "true" costs. In a more complex environment, more measurement efforts are expected to provide sufficient accuracy for product costs. Therefore, managers should be prudent in their cost information and consider cost systems' sophistication and firms' heterogeneity.

3.2 Modern cost management

3.2.1 Cost management research

Cost management is an umbrella term for making cost-related decisions on resource commitments and adjustments as well as selecting production technology (Anderson, 2006; Anderson & Dekker, 2009a, 2009b; Blocher et al., 2012). The field is inter- and multidisciplinary and unifies knowledge on management, engineering, and manufacturing. For example, management fields concentrate on managers' influence on cost behavior (Banker, Byzalov, Fang, & Liang, 2018) and the elicitation of cost structures (Anderson & Sedatole, 2013). By contrast, engineering-related fields pursue cost-effective NPD (Anderson, 2006; Davila & Wouters, 2006; Fixson, 2007) to select the best designs in a product family context (Fixson, 2007; Simpson, Jiao, Siddique, & Hölttä-Otto, 2014). Other questions concern operational improvements throughout the supply chain (Kersten, Seiter, Von See, Hackius, & Maurer, 2017; Morita, Machuca, & Pérez Díez de los Ríos, 2018; Xiong, Du, & Jiao, 2018). Overall, cost management mainly aims to efficiently handle cost trade-offs in product planning.

Cost management theory in managerial communities is based on structural and executional drivers, which should explain the impact on costs when they change (Blocher et al., 2012; Shank & Govindarajan, 1989, 1993). Structural and executional drivers belong to the suggested driver taxonomy of Riley (1987). Structural drivers refer to firms' design of products and technology. For example, drivers rise or change when introducing or changing production functions. Executional drivers relate to efficacy and efficiency in the operational stage (Shank & Govindarajan, 1993). For instance, the measurement of quality or customer satisfaction belongs to executional cost management. This perspective is further specified and verified by Anderson and Dekker (2009a, 2009b), who see structural cost management as "a decision between alternative production functions", where executive cost management improves "efficiency at a given production function"(Anderson & Dekker, 2009a, 2009b).

One aim of cost management in management accounting is to investigate sticky costs, which are a proxy for "resource adjustment costs" that affect managers' decisions (Anderson, Banker, & Janakiraman, 2003; Balakrishnan, Labro, & Soderstrom, 2014; Calleja, Steliaros, & Thomas, 2006; Guenther, Riehl, & Rößler, 2014; Weiss, 2010). Sticky costs arise from non-linear cost behavior and give insights into managers' resources commitments. When costs are sticky, one can identify less sensitive cost changes among sales decreases than increases (Banker et al., 2018). This stickiness arises from managers' behavior because they tend to retain unused resources to avoid adjustment costs. For example, firing a skilled worker may be quicker than finding a new skilled worker in terms of transaction costs. Accounting for this expectation results in resource adjustment costs, whereby managers retain resources despite sales decreases. Overall, when sticky costs are high, managers tend to keep resources longer to avoid substantial resource adjustment costs.[21] The other strand of cost management focuses on engineering disciplines, especially developing and designing cost-effective product programs (Davila & Wouters, 2004, 2006; Wouters & Morales, 2014). Cost management frequently refers to NPD (Wouters & Morales, 2014; Wouters et al., 2016), where, for instance, target costing is still a standard for cost management (Navissi & Sridharan, 2017; Zengin & Ada, 2010). Thus, NPD is at the center of making cost management decisions.

3.2.2 Cost management in NPD

Cost management in NPD concerns the cost-effective commitment of resources and production functions (Figure 16). While cost information supports decisions, it has a delay in the context of NPD. Hundal (1997) describes this as the *designer's paradox*. Later empirical evidence supports the existence of delayed effects between resource commitments and occurring costs (Ehrlenspiel, Kiewert, & Lindemann, 2002; Franz & Kajüter, 2002). Therefore, firms have the largest potential to influence future costs at the early stage of projects (Ehrlenspiel et al., 2002; Franz & Kajüter, 2002; Homburg & Richter, 2002). While NPDs are respective projects, it covers an abundant space for committing, adjusting, and determining resources and production functions around the concepts and designing phases. This ability loses its leverage over time under standard operations. Here, product costing systems start to supply cost information about the realized resource consumption.

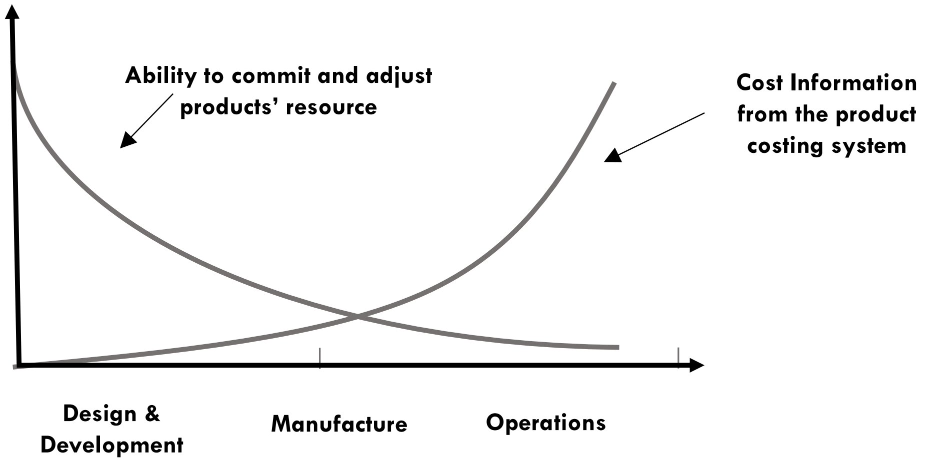

Figure 16: Conceptualized trade-off between resource commitments and costs

Developing cost-effective products has points of no return and pitfalls preventing reversible actions after design choices are made. Cost management faces the challenge that once committed, resources and production functions during NPD are merely reversible. For example, buying a customized machine for production will be hard to sell thereafter. To prevent and develop efficiently, practice thus relies on methodological instruments to systematize their inherent development routines supported by research.

[21] The sticky cost measurement mainly follows Anderson et al. (2003), with valuable extensions by Weiss (2010) and Balakrishnan et al. (2014).

Thus, many methods have evolved. Table 2 provides a condensed overview of those that promise cost-effectiveness.

Table 2: Cost management approaches in NPD following Wouters and Morales (2014)

Target Costing	Most taught on management courses, target costing is a systematic approach to develop products to a specific allowable price and margin (Navissi & Sridharan, 2017). It uses customers' perceptions of functionality in a weighted ranking that defines cost constraints for the respective components of a new product.
Value Engineering	Value engineering is a comprehensive approach that starts from the required product functions that need to fulfill quality, performance, time, and cost constraints. In particular, value is the primary target that includes the ratio of function and costs (value=function/costs).
Quality Function Deployment (QFD)	QFD starts with the identification of customer needs and expected quality. Afterward, customer satisfaction is the primary aim of all development activities (Akao, 1990). The resulting interactions among needs, engineering metrics, and components are consolidated and these describe the functional requirements. This outcome is used as a policy for product development
Design for X (DFX)	The X of DFX reflects specific aims during NPDs such as *costs*, *quality*, *ecology*, or *variety*. The respective designing procedures commonly consider products' life cycle phases as well as the identification of customer requirements (Benabdellah, Bouhaddou, Benghabrit, & Benghabrit, 2019).
Kaizen Costing	Kaizen costing, which has risen from lean principles, is the continuous pursuit of cost reductions.
Life Cycle Costing (LCC)	LCC is a cost accounting extension examining future cost streams during a product's life that is less developed in management accounting. A more practical perspective of LCC is an extension that aims to collect all data on a product during its life.
Total Cost of Ownership (TCO)	Similar to LCC, TCO is used in procurement and it includes types of transaction costs (i.e., supplier selection, supplier search, and screening).
Component Commonality[1]	Component commonality is the sharing of assets between at least two product variants.
Modular Design[1]	Modular designs provide a large product variety using sets of modules and components instead of providing variety through specific components, processes, and resources. A modular design employs combinability and functional binding to offer the same variety with less specificity.
Product Platform[1]	Product platforms are substantial sharable assets over at least one product family. In contrast to modular designs, there is a larger willingness to standardize the most common or shared components.

[1] There is no clear definition in the terminologies and a slight deviation between communities and time. Accordingly, transitions between the concepts are rather fluid than discrete.

Wouters and Morales (2014) classify cost management approaches in NPD, as illustrated in Figure 17, using a cost perspective (manufacturing costs/whole life cycle costs) and product perspective (one product vs. product family/portfolio). Under the single product perspective are approaches such as target costing, value engineering, QFD, and DFX. Kaizen costing, LCC, and TCO are similar in their perspectives but account for costs along the life cycle. In sum, all approaches ensure systematic developments that aim to achieve the cost-effectiveness of a single product. Although this leads to efficacy in the realized outcomes, it might underestimate the cost-saving effects among the product portfolio.

A broader product scope concerns the whole product portfolio or product family, where DFX is among the approaches for manufacturing costs; nonetheless, component commonality, modular design, and product platforms also have a significant impact on products' life cycle costs.[22] DFX narrows and condenses the possibilities of NPD using clearer guidance and constraints to achieve the specific goal (Fuchs & Kirchain, 2010; Wouters et al., 2016). For instance, when X means "cost", NPD emphasizes the pursuit of optimizing cost-effectiveness. An X of "variety" concerns effective NPD preventing large product variety, which refers to modularization (Blees, 2011; Blees, Joans, & Krause, 2010; Kipp, 2012). This thesis recommends the literature of Benabdellah et al. (2019) for further details.

Addressing full life cycle costs and product portfolios, methods such as component commonality, modular design, and product platforms are decisive (Wouters & Stadtherr, 2018). Among the many methods of cost management in NPD, this thesis concentrates on the gray-shaded field of modularization. Commonality, building modular designs, and platform concepts are among the most often mentioned cost-saving methods in practice and research. Thus, strategies follow the ordinary presumption of offering a large product variety at the lowest cost; however, the cost effects are firm-specific and general guidance is scarce (Campagnolo & Camuffo, 2010; Fixson, 2007; Jiao, Simpson, & Siddique, 2007; Simpson, 2004).

		SCOPE OF PRODUCTS/SERVICES	
		ONE PRODUCT	PRODUCT FAMILY/ PORTFOLIO
SCOPE OF COSTS	MANUFACTUR-ING COST	Target Costing Value Engineering QFD DFX	DFX
	ENTIRE LIFE CYCLE COSTS	Kaizen Costing Life Cycle Costing Total Cost of Ownership	Component Commonality Modular design Product platforms

Figure 17: Classification of cost management methods in NPD by scope (Wouters & Morales, 2014)

Unfortunately, the wordings and interpretations of commonality, modularity, and platforms are often interchangeably applied. This thesis sees it as follows: The main message of *commonality*

[22] DFX can be applied to a single product and product families.

expresses sharing capability. In the example of component commonality, this means that at least two products rely on the component (Collier, 1981; Salvador, 2007; Salvador, Forza, & Rungtusanatham, 2002). By contrast, *modularity* is either the property/object of a design or the characteristics of a product architecture (Campagnolo & Camuffo, 2010; MacDuffie, 2013; Salvador, 2007; Ulrich, 1995) Modularity in the design suggests the supply of a high product variety through a combination of components. Modularity in the product architecture infers that components are independent of other components and somehow differentiated. *Platforms* are large sharable assets responsible for many product variants over product families (Baldwin & Clark, 2000; Meyer & Lehnerd, 1997; Muffatto, 1999). This parallels a partial standardization of product variants through large modules with certain interfaces. Overall, offering product variety under fewer interconnections between components is associated with the usage of modules and components.[23]

Figure 18 shows the conceptual perspectives of modularity following Salvador (2007), who revisits the dimensions used in a comprehensive literature review. Modularity is mainly an object-related concept (MacDuffie, 2013). To determine its characteristics, Salvador (2007) disentangles reoccurring patterns of modularity in design to present five typical characteristics: commonality, combinability, functional binding, interface standardization, and loose coupling.

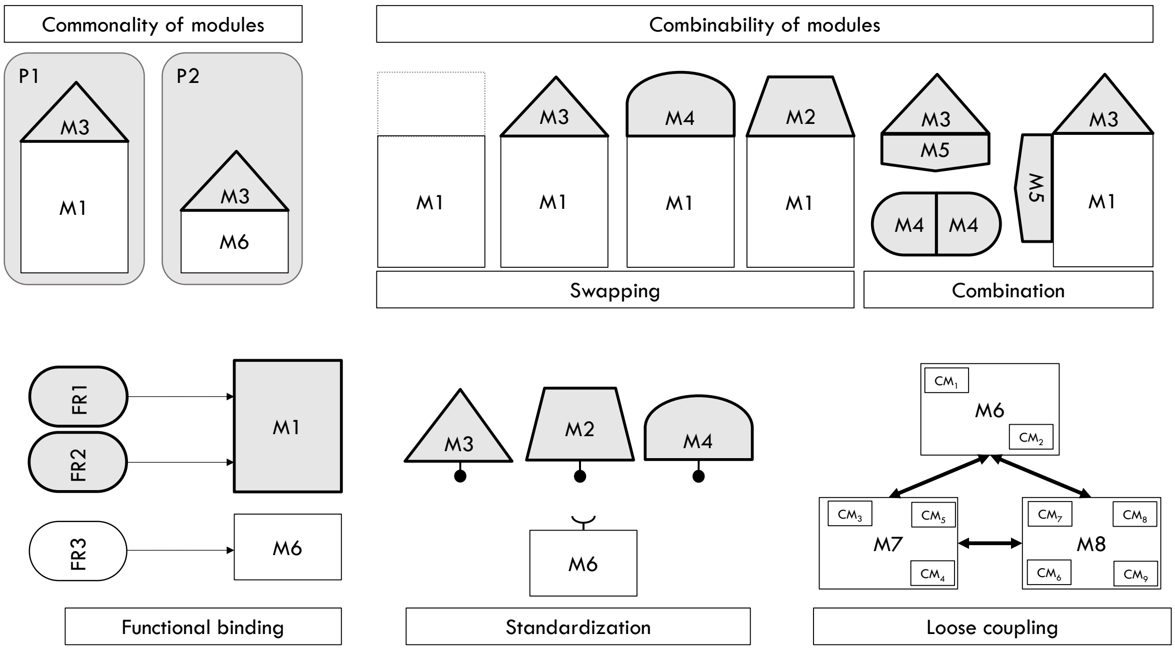

Figure 18: Conceptual description of the modularity construct (Krause, 2012; Salvador, 2007; Salvador et al., 2002) P=product, FR=functional requirement, M=module, CM=component

First, this thesis further differentiates the characteristic *combinability* into swapping and combination, as discussed by Salvador et al. (2002) and Salvador (2007). Modularity is a gradual design concept consisting of the five major characteristics shown in Figure 18. In addition, the characteristic of

[23] This thesis recognizes that modularity is not exclusively related to products because elements of processes and organizations can be modular as well (MacCormack, Baldwin, & Rusnak, 2012).

combinability is gradual as well. An extreme value of full combinability means that modules can be arbitrarily combined to construct a product variant. In the opposite direction, modules have their own combinatorial restrictions through more selective interfaces. This restriction reduces the numerical combinability because only some modules can be combined with each other. This case is known as swapping (Du et al., 2001; Salvador et al., 2002).

Functional binding is best visible from a product architecture, as modules can accumulate more than one function. This modular characteristic is striking, while it affects the contingency between modular and integral product architectures. *Standardization* is essential and this partly drives combinability and commonality. To achieve standardization, modules encourage versatile interfaces, with platforms particularly requiring ports for modules. The last principle is *loose coupling,* which is a criterion of cohesiveness defining systems as decomposable to smaller, independent, but still interrelated elements. In other words, strong couplings between elements are a primer for independent modules, where loosely couplings indicate less cohesiveness (Salvador, 2007). From a general system angle, this characteristic points to the possibility of reducing systems' complexity by having less interconnectedness and more independence (Simon, 1962).

Regardless of whether developing modules or platforms, this thesis sees modularization as a general change process in an organization starting from modular product architectures and moving toward designs, processes, and resources. Concerning the physical modularization of products, research primarily suggests a full conceptual decomposition by existing designs when analyzing potential modules (Hölttä-Otto, Otto, & Simpson, 2014; Krause et al., 2014; Krause & Gebhardt, 2018; Otto et al., 2016). Next, modularity drivers (Erixon, 1998), similarity measures (Kota et al., 2000), optimization (Luo, Tang, & Kwong, 2014), simulations (Xu & Jiao, 2014), or heuristics (Stone & Wood, 2000) are the main approaches to composite updated product family designs with new modules or platforms. Overall, modularization is thus an organization-changing process that aims to redesign existent linkages of products, processes, and the organization.

3.2.3 Modern modularization theory

Issues of modularization have been investigated from many angles (Frandsen, 2017; Gershenson, Prasad, & Zhang, 2003; Hsuan, 1999; Jiao et al., 2007; Jose & Tollenaere, 2005; Salvador, 2007; Sanchez & Mahoney, 1996), and this thesis selects studies to provide a condensed corpus of knowledge. Although all studies contribute to the literature, some have drawn stronger attention (Baldwin & Clark, 1997, 2000; Martin & Ishii, 2002; Meyer & Lehnerd, 1997; Sanchez & Mahoney, 1996; Schilling, 2000; Ulrich, 1995). Others rather examine empirical cases and field studies to collate the latest evidence from practice (Farrell & Simpson, 2009; Israelsen & Jørgensen, 2011; Marion et al., 2007; Park & Simpson, 2008; Simpson et al., 2011; Thyssen, Israelsen, & Jørgensen, 2006). Another strand – paralleling both developments – supports the methodological process of applying modularization (Gu & Sosale, 1999;

Hölttä-Otto, 2005; Hölttä-Otto & de Weck, 2007; Krause et al., 2014; Otto et al., 2016; Ripperda, 2019). This subsection provides an overview of these branches.

When discussing modularity and theory development, the work of Schilling (2000) is seminal. She conceptualizes the principal drivers of modularization in a qualitative study and claims that new products automatically request new idiosyncratic elements. Under this assumption and increasing market diversity, new products are associated with new elements in the firm and cause internal diversity. To tame this development, modularization is explained as a mechanism to reduce firms' overall specificity for management the diversity of the markets.

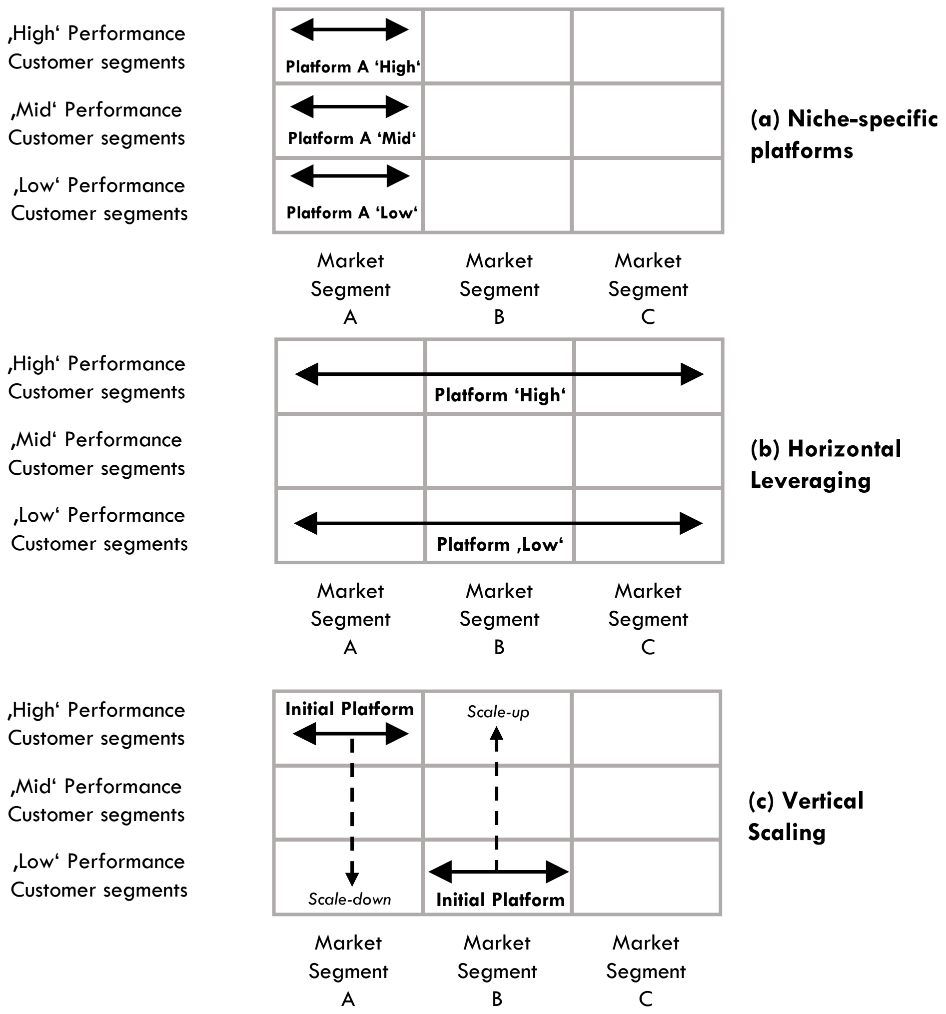

Figure 19: Market segmentation grid with strategies

Meyer and Lehnerd (1997) propose guidance on modularization strategies that align with existing market conditions.[24] They use a market segmentation grid (Figure 19) as a framework for planning and developing platforms. In detail, the grid maps customer segments to their performance, quality, or price expectations (Low, Mid, High) within a market segment. For example, a low tier incorporates basic

[24] This thesis does not demonstrate the "beachhead strategy" of Meyer and Lehnerd (1997), which is an interplay between horizontal and vertical leveraging.

requests such as minimum performance, quality, or low price, whereas High products require high performance and quality under less price sensitivity. Importantly, the grid provides actual guidance when planning modularization and platforms in product programs (Hölttä-Otto et al., 2014; Krishnan & Gupta, 2001; Kumar et al., 2008; Otto et al., 2016; Robertson & Ulrich, 1998).

In detail, based on the framework, customers have performance expectations, which are comparable to quality from an economic perspective (Anderson & Sedatole, 1998; Krishnan & Gupta, 2001; Moorthy & Png, 1992; Mussa & Rosen, 1978). Meyer and Lehnerd (1997) and Moorthy and Png (1992) were among the first to specify customer segments in terms of performance and quality, respectively. Classes should simplify the expectations of customers and their corresponding utility. In particular, Mussa and Rosen (1978) and Moorthy and Png (1992) assume that quality is proportional to the utility. Hence, higher customer utility leads to a higher potential price but higher marginal costs. This thesis also includes the assumption and recognizes higher utility proportional to marginal costs.

Moreover, the market segmentation grid also offers guidance for the strategic implementation of platforms through horizontal leveraging and vertical scaling (leveraging) (Lei & Moon, 2015; Otto et al., 2016). The simplest strategy involves a platform for every customer segment. This is known as the "niche-specific" platform strategy (a). Next, horizontal leveraging (b) aims to construct larger shared platforms across the market segments in the same performance tier. Vertical scaling (c) is a means to up- and downscale an existing platform in size, weight, or quality (Meyer & Lehnerd, 1997). This has the effect that a basic platform can target customer segments with different expectations. Overall, these strategies are relevant for planning and developing platforms and modules.

Another theoretical foundation is provided by Baldwin and Clark (2000) following Simon (1962). They argue that modularization reduces unfavorable interactions by decomposing and redesigning existing systems. In contrast to other studies, their broad systems' perspective can better explain modularity in processes, teams, and organizations (Brusoni & Prencipe, 2011; Schilling & Steensma, 2001; Sosa et al., 2003). They also claim that modules are shareable assets for interacting objects (Robertson & Ulrich, 1998) that hide unnecessary information and thus lowers perceived complexity. Moreover, they propose the first conceptual meaning of modularity, which is adapted and refined with empirical observations by Salvador (2007).

Krishnan and Gupta (2001) analytically examine both platform strategies and product introduction in accordance with the market segmentation grid. Their results propose a combined set of drivers for effective modularization. For instance, they indicate that neither low nor high market diversity supports platform and module approaches, as low diversity favors standardized products. High diversity in markets should encourage addressing only one customer segment to maximize firms' profitability. This recommendation is still in discussion (Krause & Gebhardt, 2018; Ripperda & Krause, 2017).

Ethiraj and Levinthal (2004) advance the theory by showing how modularization performs under limited information on the "true" product architecture. They show that perfect modularization in firms can only occur when all interrelations are known as well as that modularization supports complexity management. They also demonstrate that missing even small pieces of information can be decisive and find that developers and designers should minimize modularization when architectures and designs are still unclear.

The essential study by Fixson (2006) moves the product architecture to the center of attention and emphasizes function-sharing components. His study sees the product architecture as the most crucial but least investigated construct in modularization, particularly in terms of economic parameters. To improve the economic perspective on modularization, he qualitatively assesses and formalizes potential cost mechanisms such as work parallelization, economies of scale, and risk pooling. In doing so, he lists trade-offs and indicates their cost effects over the product's lifetime.

Thyssen et al. (2006) provide conceptual guidance for modularization by approximating antecedents with great potential for cost-saving effects. A first result of their empirical case study is that less unit-level dispersion among components combined with (preferably) equal demand for product variants increases the cost effects of modularization. Interestingly, they also find that the inclusion of product-specific components may lead to substantial cost savings under the assumption that all unit-level costs are equal. Another finding suggests that new modules are at least as costly as the previous costliest component. Overall, they demonstrate that commonality, unit-level costs (i.e., direct labor or material), and demand affect the module's cost-saving potential.

Empirical studies such as surveys, fieldwork, and case studies of modularization such as Pasche, Persson, and Löfsten (2011), Jacobs et al. (2011); Jacobs et al. (2007), and Danese and Filippini (2013) all argue that modularization leads to large cost savings and average performance growth. Interestingly, although modularization seemingly reduces complexity, Vickery, Koufteros, Dröge, and Calantone (2016) find in their cross-sectional study that high complexity leads to a lower performance gain under modularization. A recent study of Hackl et al. (2020) revisits the economic impact of modularity design choices and is even able to approximate the magnitudes of the relationships. The study of Van den Broeke, Boute, and Samii (2015) applies numerical explorations and stresses the trade-off between standardization and customization in a supply chain setting, finding that modularity positively affects a firm's performance and profitability.

Overall, many studies have analyzed modularization. Researchers have provided rules such as that commonality reduces production costs on average (Collier, 1981; Farrell & Simpson, 2009; Treleven & Wacker, 1987) and that minimum module costs are at least as costly as the costliest embedded component (Thyssen et al., 2006). Other studies have contributed more conceptually; see, for example, the cost product–architecture framework proposed by Fixson (2005, 2006). Despite this progress, however, questions remain, especially when considering the product architecture and market dynamics (Campagnolo & Camuffo, 2010; Fixson, 2007; Ravasi & Stigliani, 2012; Simpson, 2004).

3.2.4 Complexity costs

Another relevant and often debated topic in cost management is complexity costs (Ehrlenspiel, Kiewert, Lindemann, & Mörtl, 2014; Kersten, von See, Skirde, & Wichmann, 2015; Krause & Gebhardt, 2018; Meyer et al., 2019; Ripperda & Krause, 2017; Rosenberg, 2002; Schuh, 2005; Schuh, Riesener, Breunig, Koch, & Kuntz, 2017). Firms offer new and specialized products to increase their value and profit. Unfortunately, more individualized product variants tend to commit new or overuse existing resources, leading to greater inefficiencies and errors in the value chain. In sum, offering a product variety is associated with more complexity, which unexpectedly raises costs, termed complexity costs. Child, Diederichs, Sanders, Wisniowski, and Cummings (1991), Rathnow (1993), and Wilson and Perumal (2009) state that such complexity costs threaten competitive advantage.

Discussions on complexity costs started early in cost accounting studies (e.g., Banker, Datar, Kekre, & Mukhopadhyay, 1990; Banker & Johnston, 1993; Cooper & Kaplan, 1987; Foster & Gupta, 1990; Ittner et al., 1997), notably the trade-off between the “value of variety” and “cost of complexity” (Robertson & Ulrich, 1998; Shank & Govindarajan, 1989). Empirical studies of this topic primarily identify complexity drivers such as the number of components, the diversity of product design, production processes, portfolio width, and documentation efforts, as shown by Kersten et al. (2015) and Krause and Gebhardt (2018), and use regression-related techniques to estimate their impact on manufacturing overheads (Banker & Johnston, 1993; Banker, Potter, & Schroeder, 1995; Datar et al., 1993). Their results agree that the complexity driver can explain cost variances; nonetheless, there are distinct deviations between the drivers in these studies (Anderson, 1995; Banker & Johnston, 2006).

Although complexity costs are somewhat confirmed empirically, a concurrent formal declaration of complexity costs is lacking. The first formalized application of complexity costs outside cost accounting was by Thonemann and Brandeau (2000). They emphasize the number of mappings between product variety and processes (Thonemann & Brandeau, 2000, p. 8) as an indirect amplifying function that causes complexity costs. It is striking that their modeling almost entirely reflects the indirect overhead functions of classical cost accounting research (Christensen & Demski, 1997, 2003). A study with stronger conclusions is Ripperda and Krause (2017), who review complexity costs from an engineering perspective and define them as costs occurring in addition to existing product family structures. Their perspective is in line with Abdelkafi (2008), who shows variance-induced complexity and stresses complexity as a relative instead of an absolute measure. Therefore, firms seem to be capable of handling some degree of complexity and complexity drivers are not similar across industries.

This thesis adopts this conceptual definition by determining complexity costs as a relative measure. While each firm has inherent baseline complexity, a specific degree of additional complexity raises complexity costs. For example, let us assume state s_0 is baseline complexity in an existing product program. Introducing more products affects the components, processes, and resources and thus raises complexity. This yields the new state of s_1, which is more complex than s_0. When identifying the new costs occurring between both states, while controlling for production volume (Banker et al., 1990; Datar et al., 1993; Foster & Gupta, 1990; Ittner et al., 1997), this is likely to expose complexity costs. Conclusively, increasing complexity by $\Delta s = s_1 - s_0$ and the related cost differences $\Delta Costs = c_1 - c_0$ may be the first principle to measure complexity costs as adjustment costs for more product variety.[25]

$$\frac{s_1}{s_0} = \frac{c_1}{c_0} \tag{2}$$

One of the most recent studies of complexity costs is by Meyer et al. (2019). They present a thorough example for calculating complexity costs on behalf of increasing product variants. Their study defines the initial state s_0 by a single product firm that extends the product program by two additional variants s_1. Subsequently, variety-induced complexity increases the initial costs of c_0 with more costs c_1. Thereby, the study formalizes an increasing of complexity from variants and linked it to costs. Finally, the study proposes an approach to calculate complexity costs and prompts several new questions.

Overall, the trade-off between "product variety" and "complexity costs" remains inconclusively investigated across communities. Nonetheless, it has regained significance because of increasing cost pressure and changing circumstances in production technology. Consequently, focusing on complexity costs may lead to meaningful insights into firms' ability to be flexible and resilient.

[25] This calculation indeed parallels the measurement of sticky costs (Balakrishnan et al., 2014); Nonetheless, this thesis suggests that complexity costs have a non-monotonic relationship with complexity drivers such as increasing products, parts, documentation and many other (see Krause and Gebhardt (2018) for more drivers)

4. EAD: A theory-connecting framework

4.1 Introduction

This thesis integrates engineering design theory and economic firm theory into an EAD to formalize the "grand" product-based planning process. Today's practice is that research communities shed light on this grand process separately (Arend et al., 2017; Balakrishnan et al., 2011; Balakrishnan & Sivaramakrishnan, 2002; Robertson & Ulrich, 1998), resulting in a large and dispersed field of research mainly driven by the engineering and management communities (Anderson & Dekker, 2009a; Campagnolo & Camuffo, 2010; Fixson, 2007; Frandsen, 2017; Ravasi & Stigliani, 2012). This hampers common understandings (Tranfield, Denyer, & Smart, 2003), slows theory development (Raasch, Lee, Spaeth, & Herstatt, 2013), and dilutes research outputs (Birnbaum, 1981) due to little agreement in formalizations and modeling despite the substantial overlap in questions (Jiao et al., 2007; Simpson, 2004; Starr, 2010). Suggesting a framework under academic rigor could thus help to bridge product-based thinking across disciplines. Consequently, this thesis proposes the EAD as a theory-connecting framework for sharing and communicating concepts and formalisms beyond local engineering and management studies by rigorously modeling product-based planning.

While engineering design theory aims to optimize product designs along technical functions and parameters, the goal of economic theory is to maximize profit under the given product portfolio. The EAD is a theory-connecting framework for analyzing product-based planning processes. Considering the intrinsic motivations of both fields, it identifies related questions. Then, because an optimal product (family) design in terms of performance quality may be associated with positive economic consequences, efficient product variants or families are thus assessable using economic parameters, which may overcome the drawbacks of existing perspectives. While engineering design is ambiguous in its generality and concepts (Madni & Sievers, 2018; Starr, 2010), economic modeling can support using its critical theory development (Cooper & Hopper, 2006) and causal thinking (Gow, Larcker, & Reiss, 2016; Pearl, 2009). Likewise, economic modeling has less considered realistic product modeling, whereas engineering has less discussion in questions of capacity planning.

This thesis does not necessarily intend to propose the EAD; nonetheless, an integrated framework in both fields is lacking. Engineering design does not simply refer to the nearly unlimited possibilities of designing products (ElMaraghy et al., 2012). Searching for more formalized principles for selecting a product design leads to the axiomatic design (AD) of Suh (2001) (Gonçalves-Coelho & Mourão, 2007). However, as the AD does not explicitly cover more than one product in its decision framework, it somewhat loses contact with real cases. Additionally, the classical AD has no linkage to economic parameters such as prices, costs, capacities, and demand, despite their necessity for ranking and selecting scenarios in product-based planning (Robertson & Ulrich, 1998). In economic firm theory, there has been less discussion about interdisciplinary effects between products or couplings between customer' needs and respective functions. In detail, products are frequently independent outputs of production functions. While this is not false per se, the theory is likely to oversimplify a product's subtle network of customers, functions, and design. To sum up, there are as many opportunities to benefit from integrative framework to answer questions of product and production planning.

4.2 Theory integration

Integrating engineering design theory (also known as model-based system engineering or model-based engineering) (ElMaraghy et al., 2012; Van der Auweraer, Anthonis, De Bruyne, & Leuridan, 2012) with economic firm theory is the foundation for the EAD. First, under economic firm theory, profit maximization is the central motivation for decisions (Christensen & Hemmer, 2006; Demski, 2008). To maximize profit, firms either maximize the sales of products, minimize their costs, or both (Demski, 2008; Shepard, 2015). Formalizing both economic objectives within a profit maximization proposition Π pertains to the sub-objectives of sales maximization (output prices multiplied by demand $\widehat{\boldsymbol{\rho}}\boldsymbol{q}$) and cost minimization (input price multiplied by the required input resources $\boldsymbol{\rho x}$) under realized demand q. Both sub-objectives together determine the profit maximization function $\Pi(\widehat{\boldsymbol{\rho}}, \boldsymbol{\rho})$ in equation (3). This equation is fundamental to firms' motivation for large and small decision problems (Christensen & Hemmer, 2006; Demski, 2008).[26]

$$\Pi(\widehat{\boldsymbol{\rho}}, \boldsymbol{\rho}) = \max_{\boldsymbol{q}} \widehat{\boldsymbol{\rho}}\boldsymbol{q} - \min_{\boldsymbol{x}} \boldsymbol{\rho x} \tag{3}$$

Hence, assuming realized demand $\boldsymbol{q}$ for firms' output determines the necessary number of input resources $\boldsymbol{x}$ for supplying the output $\boldsymbol{y}$. Imagine customers are going to buy bikes, expressed as $\boldsymbol{y}$, at the quantity of $\boldsymbol{q}$. The firm receives realized demand $\boldsymbol{q}$ that prompts the production technology $\boldsymbol{T}$ for producing outputs $\boldsymbol{y}$ at the number of $\boldsymbol{q}$. The production functions can supply the output when they have the necessary total input resources $\boldsymbol{x}$. The number of inputs refers to the minimum requirements $\boldsymbol{\lambda}$ within each production function multiplied by demand ($\boldsymbol{x} = \boldsymbol{\lambda q}$). Finally, the production technology $\boldsymbol{T}$ transforms the total input resources $\boldsymbol{x}$ (i.e., wheels, frames, working hours) into bikes $\boldsymbol{yq}$ (Christensen & Hemmer, 2006). This relationship is frequently described by inequalities and thereby embeds the input/output transformation constraint shown in equation (4).[27]

$$\boldsymbol{yq} \leq \boldsymbol{T}(\boldsymbol{x}) \leq \boldsymbol{T}(\boldsymbol{\lambda q}) \tag{4}$$

[26] Profit maximization assumes the non-adjustable output $\hat{\rho}$ and input prices ρ in accordance with polypolistic internal and external markets (Christensen & Demski, 1997).
[27] When capacities are assumed to be perfect, resource minimization is infeasible. Consequently, resource minimization develops into a necessary resource demand with input prices that is also a cost function p_c. Thus, there is a pull of the inequality of $\boldsymbol{yq} \leq \boldsymbol{T}(\boldsymbol{x})$.

Total input resources $\boldsymbol{x}$ depend on the requested output $\boldsymbol{y}$ (Fandel, 2005; Shepard, 2015) but their minimization also reflects the cost function of $\boldsymbol{c_f}(\boldsymbol{\rho}, \boldsymbol{q})$. Cost functions recognize the total input resource consumption $\boldsymbol{x}$ with their corresponding input prices for supplying cost information. Taking this micro-level assumption to total consumption in the production technology $\boldsymbol{T}$ yields firms' total costs. Concerning profit maximization in equation (**3**), the cost function and production technology can replace the minimization problem. This changes equation (**3**) to equation (5) (Christensen & Hemmer, 2006). Equation (5) is central; it depicts the final profit maximization as a function of demand $\boldsymbol{q}$, output price $\widehat{\boldsymbol{\rho}}$, input price $\boldsymbol{\rho}$, and specific production technology $\boldsymbol{T}$. The profit maximization of a multiproduct firm in equation (5) is the foundation for designing the EAD as a decision-making framework that integrates engineering design theory.

$$
\begin{gathered}
E\ (\widehat{\boldsymbol{\rho}}, \boldsymbol{\rho}) \ =\ \max_{\boldsymbol{q}} \widehat{\boldsymbol{\rho}}\, \boldsymbol{q} \ -\ \boldsymbol{c_f}(\boldsymbol{\rho}, \boldsymbol{q}) \\
subject\ to\ \boldsymbol{yq}\ \leq\ \boldsymbol{T}(\mathbf{x})
\end{gathered}
\tag{5}
$$

Management accounting and production theory have strongly elaborated and formalized questions of production and capacity planning. In this respect, cost accounting studies are no exception and set the state of the art (Anand et al., 2019; Balakrishnan et al., 2011; Christensen & Demski, 1997; Labro & Vanhoucke, 2007). Those studies divide production technologies into the three stages of products, processes, and resources. This differentiation is helpful because cost investigations underlie resource consumption patterns from production functions. Whereas processes and resources are sufficiently detailed for cost studies, products are neither specifically modeled in these studies (Anand et al., 2019; Labro & Vanhoucke, 2007, 2008) nor strongly mentioned in profit maximization. This lack of product modeling limits the theory of engineering design research.

To use profit maximization as a motivation for decisions in a broad product-based planning concept, product modeling is necessary. Again, economic firm theory does not describe products to a large extent; instead, they are abstracted to unrealistic simplicity. Moreover, there is less discussion about product modeling and it does not continue to look beyond process outputs as the final products (Anand et al., 2019; Balakrishnan et al., 2011; Christensen & Hemmer, 2006). Engineering-related research sees products not as a simple direct output of the production technology (Akao, 1990; Fisher et al., 1999; Martin & Ishii, 2002; Stone & Wood, 2000). Products are rather complex constructs of various functions and design characteristics for satisfying customer needs (Du et al., 2005; Ulrich & Ellison, 1999; Xu et al., 2009). Consequently, this thesis uses the AD of Suh (2001) to extensively model the output $\boldsymbol{y}$ to a product construct supplied by an enriched production technology $\boldsymbol{T}$.

Engineering design theory describes the output of the production technology $\boldsymbol{y}$ as product constructs instead of as a simple process output. Although product has been a valuable abstraction in economics fields, it mitigates cross-domain questions. Building this bridge focuses on the EAD because it enriches production technology $\boldsymbol{T}$ through the AD, which is a formalized and mathematical technical design theory for constructing optimal product designs necessary when designing new products or initiating redesigns of existing variants. As a result, the EAD incorporates the customer, function, and design perspectives to model product constructs at the product portfolio level.

Finally, equation (6) substitutes $\boldsymbol{T}$ with $\boldsymbol{EAD}$, where the output $\boldsymbol{y}$ reflects the portfolio of product constructs, triggered by customers, consisting of functions and physical design relations.

$$E(\widehat{\boldsymbol{\rho}}, \boldsymbol{\rho}) = \max_{\boldsymbol{q}} \widehat{\boldsymbol{\rho}}\, \boldsymbol{q} - \boldsymbol{c}_f(\boldsymbol{\rho}, \boldsymbol{q}) \qquad \textbf{(6)}$$
$$Subject\ to\ \boldsymbol{yq} \ \leq\ \boldsymbol{EAD}(\mathbf{x})$$

In short, the EAD integrates engineering design theory and economic firm modeling. When seeking to cover the entire picture of product-based planning, it requires a decision framework for product designing and production planning. Therefore, it seems right to combine both theories despite this posing a myriad of new questions.

4.3 Classical AD

Before introducing the EAD, it is necessary to understand the axiomatic mathematical principles of the AD. Formalizing and describing the nature of a system builds upon axiomatic principles (Adams et al., 2014). They also build a fundament for deductive reasoning and modeling while embedding logical – somehow unquestionable – argumentations by math. Therefore, the AD relies on mathematical set theory (Kuratowski & Mostowski, 1976).

Figure 20 illustrates the "design world" of the AD with all its corresponding domains (Suh, 1995, 1998, 2001). No matter the design context, the "left domain" is the question of "what we want to achieve". The corresponding "right domain" is "how we propose to satisfy this (design) requirement". It starts with customer needs (***CN***), which invoke a "pull system" of functional requirements (***FR***). Then, each ***CN*** is what firms want to achieve, where ***FR*** are the requirements. The mapping between them can be seen as a requirement matrix paralleling approaches such as QFD (Chan & Wu, 2002). Overall, Figure 20 includes all the domains to provide a full overview.

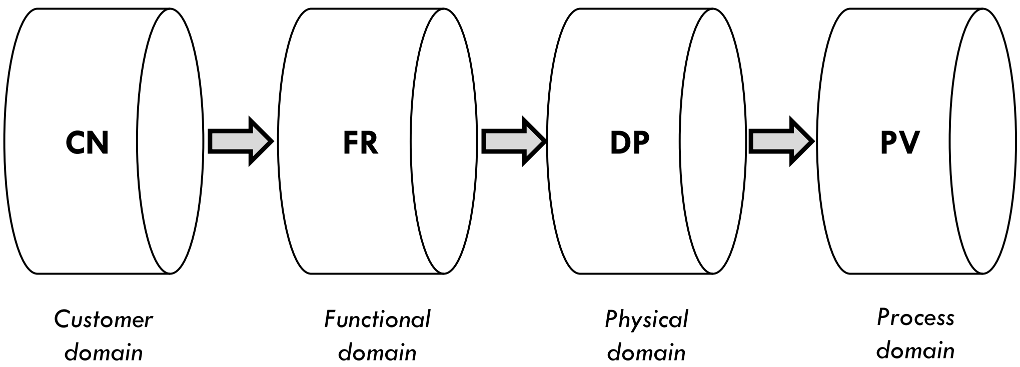

Figure 20: Conceptual AD

The AD follows the hierarchical system principles of Simon (1962) and uses domain (parameter) mappings to formalize a system. As introduced in Section 4.32.1.2, the AD fits conceptually to the hierarchical system construct. Following Adams et al. (2014), every system has a depictable design in terms of domains and functions. Thus, domains are decomposable as a system of equations referring to *design matrices* $\boldsymbol{A}$. This design matrix in turn connects the independent parameters $\boldsymbol{x}$ to particular sets of the dependent parameters $\boldsymbol{y}$. Consider a design matrix $\boldsymbol{A_{FR\_DP}}$ that maps a set of functional requirements $\boldsymbol{FR}$ to subsequent design parameters $\boldsymbol{DP}$ ($\boldsymbol{FR} = \boldsymbol{A_{FR\_DP}}\,\boldsymbol{DP}$). The single numerical example of $A_{FR\_DP} = 5$ implies the mapping of $FR_1 = 5DP_1$. Of course, more interconnected mappings such as $FR_1 = 3DP_1 + DP_2 + 2DP_3$ are possible, which the design matrix A_{FR_DP} embodies. As long as the system is linear, design matrices have constant values. In the case of non-linearity, constant values are autonomous subfunctions (Suh, 2005), which gives space to adapt realistic cases, including their enormous complexity. However, this thesis focuses on linearity to ensure the concise communication of the core ideas.

The actual usage of the AD demands a conceptual understanding (Gonçalves-Coelho & Mourão, 2007; Jiao et al., 2007), empirical terminology (Guenov & Barker, 2005; Gumus, 2005), and optimization (Cebi & Kahraman, 2010; Thielman & Ge, 2006). Kulak, Cebi, and Kahraman (2010) provide a comprehensive literature review on the AD’s applications. They show that the AD is particularly decisive for questions of product design (Tseng & Jiao, 1997) and seemingly vital as a conceptual skeleton. For example, Jiao et al. (2007) use the domains of the AD as a conceptual framework structuring their literature review. Finally, the AD has been widely explicitly and more often implicitly acknowledged and applied.

4.4 Conceptual EAD

Figure 21 illustrates how and where the EAD merges engineering design theory with economic firm theory. The EAD consists of three conceptual modules concerning the essential stages of product-based planning. First is the *product portfolio definition* (see Sections 2.2.1 and 2.2.2 for more details), which is the initial step in product planning. Second, defining the product portfolio requires determining the designs of many products, summarized as *product (family) designing*. This is the next step in product-based planning. Lastly, the module of *production technology* incorporates the existing production layout and structure including the processes and capacities.

In pursuing engineering design theory, the product portfolio definition and product (family) designing rely on the parameters of customer needs (***CN***), functional requirements (***FR***), and design parameters (***DP***), where economic firm theory supports the formalism of activities (***AV***), resources (***RC***) and related economic parameters.[28] While products are simplified from an economic perspective, the EAD partially incorporates the AD to overcome this oversimplified perspective. Specifically, ***CN***, ***FR***, and ***DP*** provide an excellent supplement to and extension of modeling products, where the point of merging the theories takes place at the end of ***DP*** (referring to the AD) and at the end of products ***P*** from an economic modeling perspective. Overall, this connection secures sufficient product modeling in engineering disciplines where the production technology satisfies economic-related fields. The conceptual depiction in Figure 21 illustrates merging engineering design theory with economic firm theory.

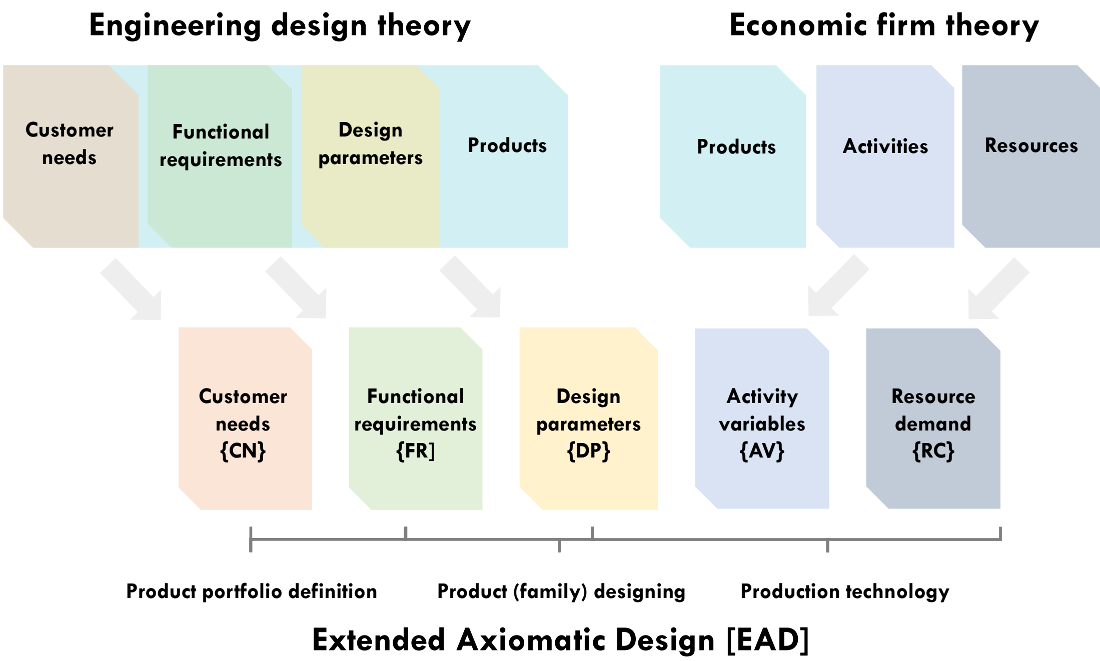

Figure 21: Merging engineering design and economic firm theories to create the EAD

[28] Economic theory frequently uses activities instead of processes. The thesis use both interchangeable.

A **product portfolio definition** can be formally expressed as the mapping between customers' needs ***CN*** and products' functional requirements ***FR***. It is assumed that the product portfolio definition starts from the market side, known as top-down product planning (Krause & Gebhardt, 2018; Otto et al., 2016; Ulrich & Eppinger, 2012). As a first step, the marketing department differentiates the market into segments and clusters them by their needs. This segmentation also disentangles targetable customer segments with better knowledge about their wishes and expectations (Du et al., 2005; Meyer & Lehnerd, 1997; Ulrich & Ellison, 1999). The more customers overlap in their set of needs, the larger the expected demand q of a segment, where firms target such segments by providing new product variants (Du et al., 2001, 2005; Ulrich & Ellison, 1999).

Every product in a portfolio is a construct of the functional requirements ***FR*** and design parameters ***DP*** for an appropriate **product (family) design**. Design parameters ***DP*** are engineering and construction metrics such as the necessary conditions, tolerances (i.e., temperature tolerance of ±0.1°), and employee skill requirements (i.e., capable of analyzing the data) in services. In general, ***DP*** need not be a physical object. Instead, it can be intangible such as digital knowledge or information. In this stage, the EAD also highlights that components (***CM***) are constructs of ***DP*** (Baldwin & Clark, 2000). Such aggregation, as suggested from the EAD as an additional formalism, overlaps with other frameworks (Du et al., 2001; Kipp, 2012; Krause & Gebhardt, 2018; Martin & Ishii, 2002; Ulrich & Ellison, 1999) and supports product architecture modeling at a higher level (i.e., mapping ***FR*** to ***CM***).

The final set of domains originates from economic firm modeling concerning **production technology**. Each ***DP*** or respective ***CM*** is related to processes ***AV*** such as procurement and indirect production activities. The structure of all ***AV***, namely the technology, reacts to the demand request and prompts processes ***AV*** that demand resources ***RC***. The classical AD entails process variables ***PV***; however, they have not yet been intensively discussed or applied. In addition, it lack the principles of economic theory referring to neoclassical production and cost theory. Thus, ***PV*** is substituted by the activity variables ***AV*** employing production theory and its functions. The resource demand is the last step of the EAD, highlighting the consumption of material, labor, and required capacities in general.

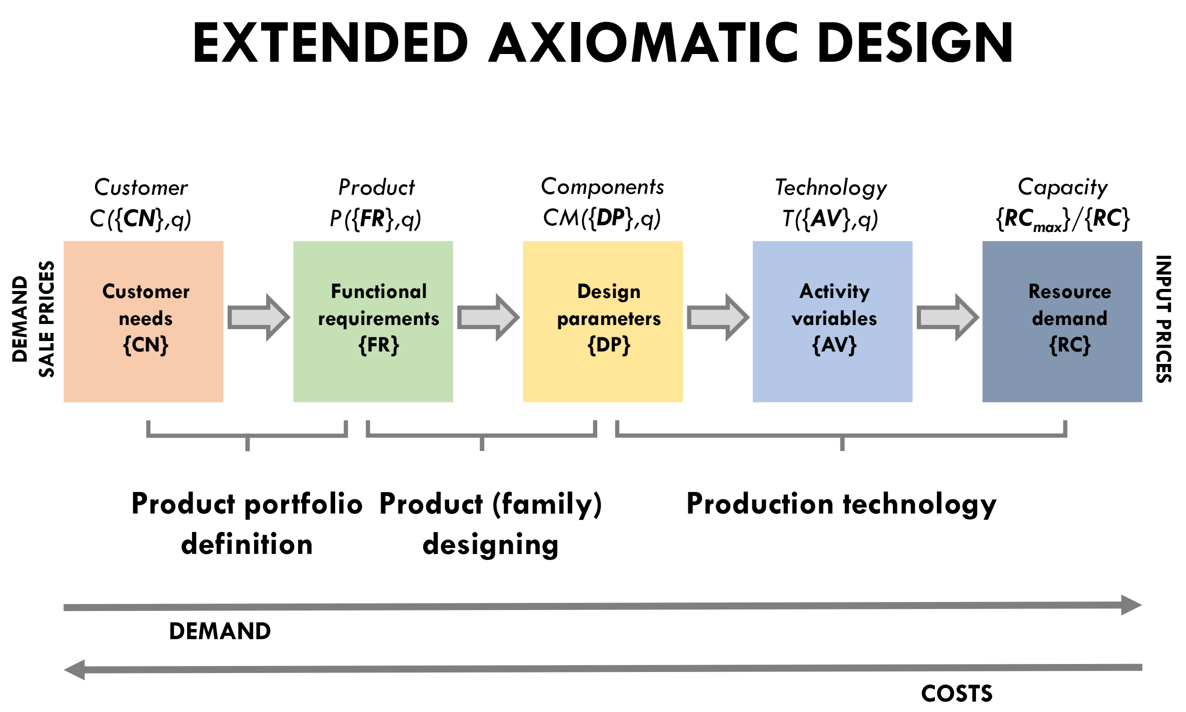

Figure 22: Conceptual EAD

Connecting all three modules leads to the final conceptual EAD in Figure 22, which incorporates a profit maximization motivation concerning demand and costs. The EAD surrogates a standard production technology but is extended through engineering design theory. Profit maximization implies total demand for pre-existing structures that diffuse through the EAD toward final resource consumption. Combining final resource consumption with input prices further weights the previous elements and leads toward final product costs.

4.5 Designing and formalizing an EAD

4.5.1 Product portfolio definition

Designing an EAD develops a nearly complete product program under profit maximization. The actual sections follow the top-down approach of product-based planning, while gradually explaining and formalizing the levels of the EAD. Figure 23 depicts the product portfolio definition, which includes the trade-off of aligning firms' products ***P*** [1 x *Ps*] with customer segments ***C*** [1 x *Cs*]. Under engineering design theory, this trade-off has finer granularity (AlGeddawy & ElMaraghy, 2013). There, products and customers are constructs of the parameters ***FR*** and ***CN***, respectively. Subsequently, one product *P* contains several ***FR*** [1 x *FRs*] $P(FR_1, FR_2, ..., \boldsymbol{FR})$, where a customer segment *C* similarly contains ***CN*** [1 x *CNs*] $C(CN_1, CN_2, ..., \boldsymbol{CN})$. This is the lowest level of granularity responsible for the alignment between ***P*** and ***C*** based on ***FR*** and ***CN***.

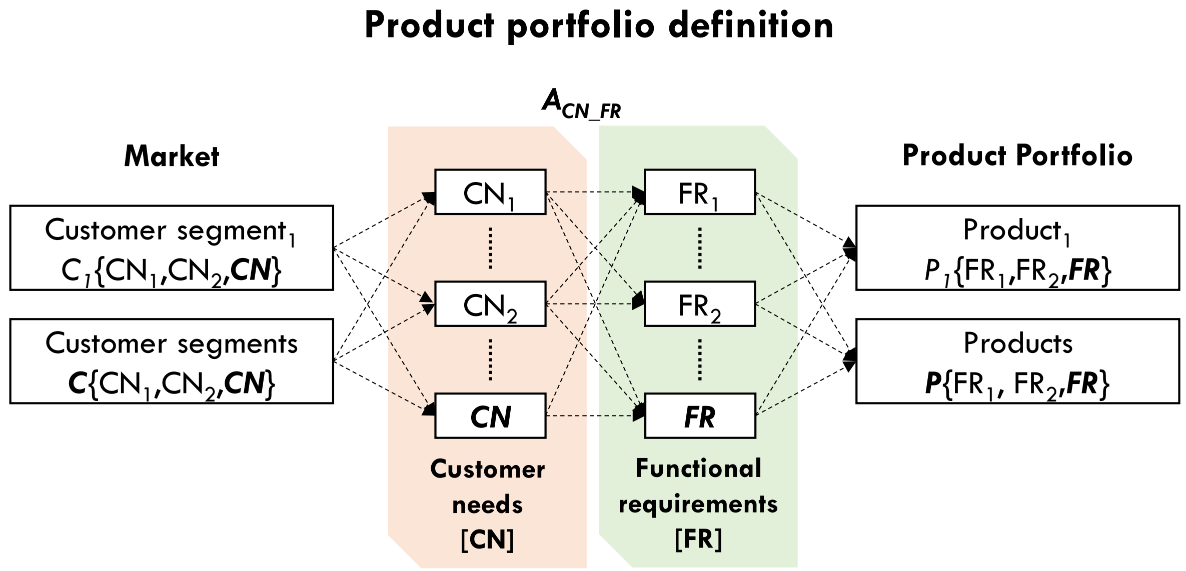

Figure 23: EAD – Product portfolio definition

Defining the product portfolio starts with the identification of customers' needs, which prompts a detailed understanding, segmenting, and thorough targeting of the market (Kotler & Keller, 2015). Following previous studies (Akao, 1990; Du et al., 2001, 2005; Luchs & Swan, 2011; Stone & Wood, 2000; Ulrich & Ellison, 1999), the EAD determines $\boldsymbol{C}$ as unique sets of customer needs $\boldsymbol{CN}$ ($\boldsymbol{C}(\boldsymbol{CN})$). In line with economic firm modeling, the more individual customers in a segment, the larger demand $\boldsymbol{q}$ [1 x Cs] ($\boldsymbol{C}(\boldsymbol{CN},\boldsymbol{q})$).

$$\begin{gathered}\boldsymbol{C}(\boldsymbol{CN},\boldsymbol{q}) \leq \boldsymbol{P}(\boldsymbol{FR},\boldsymbol{q}) \\ \boldsymbol{CN} \leq \boldsymbol{A}_{\boldsymbol{CN\_FR}}\,\boldsymbol{FR}\end{gathered} \tag{7}$$

The alignment between customers and products addresses how well each $\boldsymbol{FR}$ satisfies the respective $\boldsymbol{CN}$. Again, products are sets of attributes, functions, or engineering metrics (Fisher et al., 1999; Gershenson et al., 2003; Martin & Ishii, 2002). This aligns with the structure of customer segments, where products $\boldsymbol{P}$ are constructs of $\boldsymbol{P}(\boldsymbol{FR})$. In the simplest case, there are binary fits between $\boldsymbol{CN}$ and $\boldsymbol{FR}$, resulting in 0% for no fit and 1 for 100% fit. For instance, imagine one customer $C(CN_1, CN_2)$ that wants to "drive a fast car" (CN_1) "in the color red" (CN_2). Having a corresponding product $P(FR_1, FR_2)$ "a fast red car", the customer will purchase and will have 100% satisfaction $\boldsymbol{P}(\boldsymbol{FR},\boldsymbol{q})$. Equation (7) exemplifies this alignment between customers and products by referring to the underlying micro-level mapping between $\boldsymbol{CN}$ and $\boldsymbol{FR}$ mapped by $\boldsymbol{A}_{\boldsymbol{CN\_FR}}$. To sum up, the design matrix $\boldsymbol{A}_{\boldsymbol{CN\_FR}}$ maps the requested functions with customer needs, which is close to a requirement matrix in QFD (Tang, Y.K.

Fung, Xu, & Wang, 2002). However, the limited information on customers' needs, utility expectations, and missing alignments may be relevant in further research.[29]

4.5.2 Product (family) designing

Product (family) designing is based on mappings in the design matrix $\boldsymbol{A_{FR\_DP}}$ between products' functional requirements ***FR*** to their necessary design parameters (***DP***). Figure 24 depicts the formalized relationships between products ***P***(***FR***) and components ***CM***(***DP***), including different levels of granularity. Naturally, ***FR*** need technical or service mechanisms to fulfill their specific purposes (Kipp, 2012; Krause & Gebhardt, 2018). ***DP*** [1 x *DPs*] cover this concept in the most granular form and are valuable for finding the optimal designs (Suh, 2001). Nonetheless, the majority of studies refer to components (***CM***) as their reference unit (Blees, 2011; Kipp, 2012; Krause & Gebhardt, 2018; Otto et al., 2016; Ulrich & Ellison, 1999). While compliant components are aggregates of ***DP*** in the EAD, the design matrix A_{FR_DP} can be similar to the product architecture of Ulrich (1995).

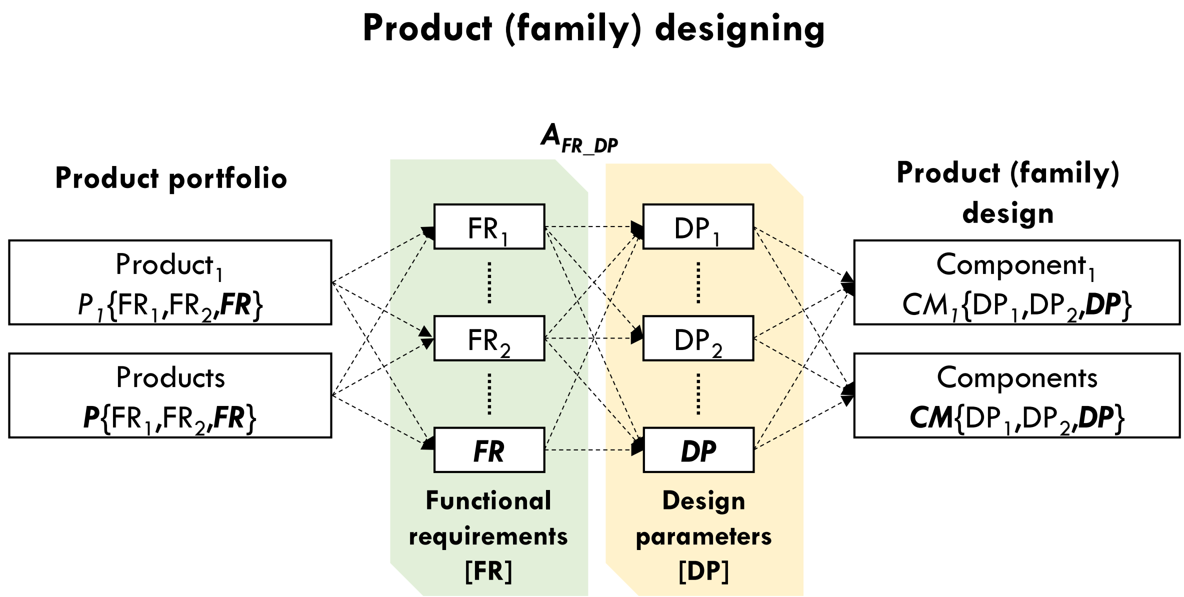

Figure 24: EAD – Product (family) designing

$$\boldsymbol{P}(\boldsymbol{FR},\boldsymbol{q}) \leq \boldsymbol{CM}(\boldsymbol{DP},\boldsymbol{q})$$
$$\boldsymbol{FR} \leq \boldsymbol{A_{FR\_DP}}\,\boldsymbol{DP} \tag{8}$$

[29] The EAD does not yet account for the utility functions between expected and realized expectation $u(CNs, FRs)$ or willingness to pay. There is thus much potential for further research (Du et al., 2005; Homburg & Stock-Homburg, 2012; Xu et al., 2009). For instance, customer satisfaction is a crucial key performance indicator under several theories such as prospect theory, attribution theory, and kano modeling (Homburg & Stock-Homburg, 2012; Xu et al., 2009). In addition, cost changes can affect price mechanisms (i.e., cost-based pricing), where willingness to pay covers customers' price sensitivity (Hanemann, 1991). In the considered cases, the fit between functional requirements and utility expectations is perfect and customers have unlimited willingness to pay.

Equation (8) demonstrates products' functional requirements demand – as opposed to the AD – for the ***CM*** [*1 x CMs*] components. The requirements of ***FR*** to ***DP*** belong to mappings in the design matrix A_{FR_DP}. Given the example of an electronic circuit board with numerous elements, there are many potential ***DP***. Hence, it is possible to define a ***DP*** for the resistance tolerances or an earthing subsystem. Nonetheless, this level of granularity may overlook practicable sensibility because questions of firms' product programs mainly refer to components ***CM***; see, for example, the module interface graph of Krause et al. (2014), DSM modeling of Eppinger and Browning (2012), and variety allocation model of Kipp (2012). Consequently, ***CM*** are constructs that encompass many or at least one ***DP***.[30]

Accepting this argumentation, $\boldsymbol{A_{FR\_DP}}$ maps ***FR*** to ***DP*** or to **CM** by $\boldsymbol{A_{FR\_CM}}$, where the component perspective mirrors the product architecture of Ulrich (1995). $\boldsymbol{A_{FR\_DP}}$ covers one of the most crucial interfaces when considering efficient product (family) designing (Fixson, 2006; Jiao & Tseng, 2000; Sharman & Yassine, 2004; Skirde, Kersten, & Schröder, 2016; Ulrich & Eppinger, 2012). This is somewhat new, as the classical AD does not explicitly consider full families or portfolios, and extending it may thus be fruitful. In particular, research investigates efficient product (family) designs instead of single products. Thus, the EAD extends and emphasizes product (family) architectures (Du et al., 2001; Erens & Verhulst, 1997; Jiao et al., 2007; Jiao & Tseng, 1999).

4.5.3 Production technology

The final stage of the EAD (product technology) entails economic firm modeling by the components required ***CM*** [1 x *CMs*] from the design parameters ***DP*** [1 x *DPs*] to activity variables ***AV*** [1 x *AVs*] toward input resources ***RC*** [1 x *RCs*]. Production theory suggests modeling an economic production environment by employing outputs (here, design parameters ***DP*** or components ***CM***), processes, and input resources (Christensen & Hemmer, 2006; Shepard, 2015). Here, among others, cost accounting studies are state-of-the-art for modeling (Anand et al., 2019). The EAD includes their contributions by mapping ***CM*** to ***AV*** toward ***RC*** in accordance with their guidance. As a result, the two design matrices $\boldsymbol{A_{CM\_AV}}$ and $\boldsymbol{A_{AV\_RC}}$ map ***CM***, ***AV***, and ***RC***, yielding the total resource consumption demand.

[30] All the parameters (*CN*, *FR*, *DP*, *AV,* and *RC*) can have their own structures consisting of flows or couplings, identifiable through a DSM. While this would complicate an introduction, there is no limitation per se. For simplicity, the EAD assumes full decoupling (identity matrices).

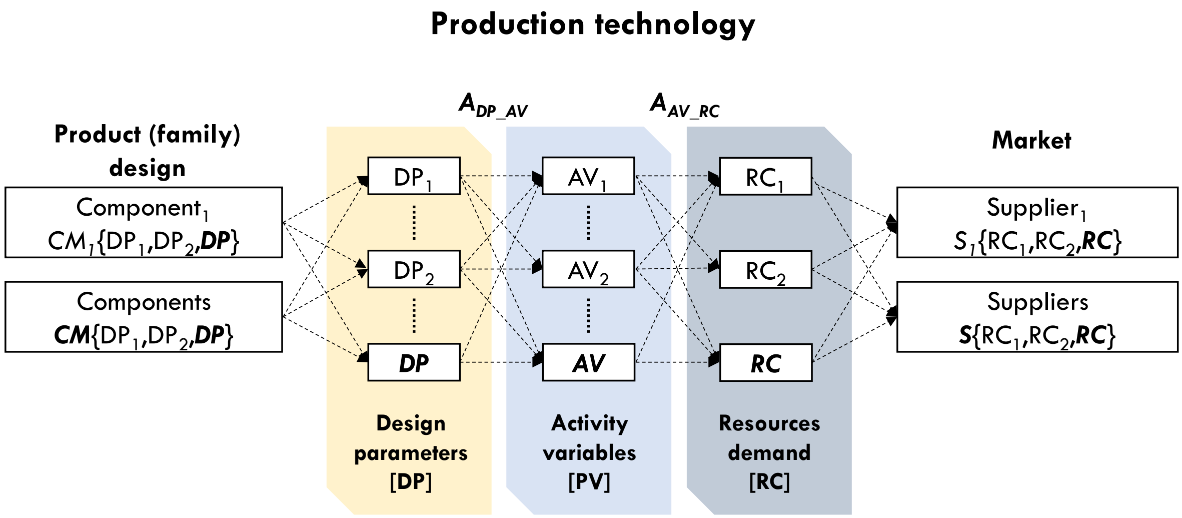

Figure 25: EAD – Production technology

The EAD in Figure 25 defines the output of the production technology as ***DP*** or ***CM*** to link it to the product portfolio definition and product family design. Following economic firm modeling, the demand ***q*** of ***CM*** prompts processes ***AV*** and resources ***RC*** for production (***CM(DP,q)*** ≤ ***AV***(***RC***,***q***)). The first design matrix $\boldsymbol{A_{DP\_AV}}$ pertains to the mapping of ***DP*** to ***AV***, where every ***AV*** is a specific production function. While every production function is unique, some ***DP*** require fewer processes than others. Nonetheless, all ***AV*** behave proportionally to realized demand ***q***. Thus, the larger demand, the larger the total required output of the production functions.[31] Equation (9) records the aggregated behavior of firms' production technology concerning the components detailed by design matrices (1) and (2). The final resource domain hence supports the functions for supplying the required components.

$$\boldsymbol{CM}(\boldsymbol{DP},\boldsymbol{q}) \leq \ \boldsymbol{AV}(\boldsymbol{RC},\boldsymbol{q})$$
$$\boldsymbol{DP} \leq \boldsymbol{A_{DP\_AV}}\ \boldsymbol{AV}$$
$$\boldsymbol{AV} \leq \boldsymbol{A_{AV\_RC}}\ \boldsymbol{RC} \tag{9}$$

In summary, the design process of an EAD begins by targeting customer segments ***C(CN,q)*** for the product portfolio definition. In the optimal case, every segment has a corresponding product that perfectly fits the needs with its functional requirements ***P***(***FR***,***q***). Subsequently, the functions refer to specific sets of components ***CM(DP,q)***, where both include firms' product architectures. Overall, their mappings reflect the product (family) designs. While demand diffuses toward production, this prompts the technology to supply the necessary components. Production consists of processes ***AV*** and resources ***RC***, which end up in outputs ***AV***(***RC,q***). Eventually, the final amount of required input resources is set.

[31] When discussing manufacturing, issues of scheduling and material flow are also important. In accordance with operations management, here, modeling is divided into two directions. The first direction refers to scheduling and queuing problems. Here, Little's law (Little & Graves, 2008) is a basic theory for investigating the efficiency of flows and productivity. By contrast, this thesis assumes the full utilization of capacities and adopts a second path without addressing continuous flows in manufacturing. Overall, the EAD can account for Little's law but the underlying research objectives do not require this.

Without capacity restrictions, each consumption has its price and this will cause costs. These resource costs are retractable in the EAD across all earlier design elements. This also adds the economic context to engineering design, mirroring all aspects of product-based planning. Overall, the EAD thus proposes a theoretical foundation for product-based planning that combines the principles of engineering design with those of economic firm theory.

4.5.4 Applying the EAD

This section uses a simplified practical example with two products, which consist of two ***FR***, three ***CM***, four ***AV,*** and five ***RC***, to give an overview of applying the EAD. The case concerns the product family program of 'main controller units' (MCUs) consisting of the two respective variants with cold resistance or not. MCUs are central processing units of electrical signals and control several functions (e.g., enabling steering of a vehicle or safety control). This thesis simplifies all possible ***FR*** to the single function of "central processing". So, if customers wish for CN_1 "control", they will require FR_1 'central processing". Next, FR_1 prompts the ***CM*** "housing" and "circuit board". Both housing and circuit board ***CM*** are in-house produced and will require ***AV*** and ***RC***. Therefore, they also request for the housing process, board assembly and quality testing. The processes, in turn, are contingent on specific sets of ***RC*** (i.e., material housing, labor hour housing, or engineering hour). In sum, the practical example illustrates a small product program.

While one product is depictable by the classic AD, the example will additionally cover for a second *CN* of "cold protection" (CN_2). Extending the product program of the standard MCU by another MCU with protection against cold, given by CN_2, conducts a new FR_2. The FR_2 can consist of new or existent elements that influences the number and usage of forthcoming components, processes, and resources. Before proceeding, this example assumes that each *CN* has one respective *FR*, consequently $A_{CN\_FR}=1$. Following the previously made formalizations, the two customers define two products (see Equation (10) and Figure 26). Then, the practice example consists of two MCUs, 'standard' and 'cold housing', where the latter requires more testing time and specific parts.

$$A_{C\_CN} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} = A_{FR\_P} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$$

$$C_1('electrical\ management') \leq P_1('central\ processing')\ ;$$
$$C_2('eletrical\ management','\ cold\ resistant') \leq P_2('central\ processing','cold\ protection') \quad (10)$$

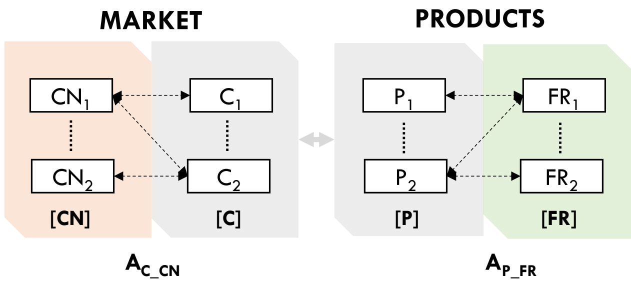

Figure 26: EAD from the aggregated market and product perspective

Table 3 shows the minimum design and related costs for one product unit of each product by means of the EAD. Table 3 primarily overviews but also quantifies the introduced example of the MCU variants by adding prices to all resources (e.g., one material housing costs 0.50€, one engineering hour 2€, thermal insulation 2€). Additionally, it shows that weights of mappings must not necessarily be one. Because the testing of the cold protection takes more time than the standard processes, *CM* "cold housing" requires two instead one testing run. In sum, the example confirms that the EAD depicts a product program by accounting for its design and costs.

Table 3: Example of EAD consisting of engineering design and economic measures

CN	***FR***	#	***CM***	#	***AV***	#	***RC***
control (CN_1)	central processing (FR_1) [5€]	1	housing (CM_1) [1.5€]	1	housing process (AV_1) [1.5€]	1	material housing (RC_1) [0.5€]
						2	labor hour housing (RC_2) [0.5€]
		1	circuit board (CM_2) [3€]	1	board assembly (AV_2) [1€]	2	material board (RC_3) [1€]
						1	worker board (RC_4) [1€]
				1	testing (AV_3) [2€]	1	engineering hour (RC_5) [2€]
cold-resistant (CN_2)	cold protection (FR_2) [4€]	1	cold housing (CM_3) [4€]	1	housing adjustment (AV_4) [2€]	1	thermal insulation (RC_6) [2€]
				2	testing (AV_3) [1€]	1	engineering hour (RC_5) [2$]

Assume that the demand *q* of each product is one, the standard MCU will cost 5€, whereas the cold-resistant MCU costs 9€. Offering a new function for customers, designed as the FR_2, results in additional costs for the firm. Specifically, thermal insulation and quality testing are additionally required that leads to greater costs. Hence, the product costs of the standard MCU are by 4€ higher than the standard MCU. Under the linearity condition, product costs will increase proportionally by the demand (i.e., q_1=5 resulting in total product costs for the standard of 25€ (5·5€)), whereby the EAD can eventually calculate firms' total costs in consultation with product variety.

The Equation (11) shows the resulting matrix notations from the EAD, which starts from ***CN*** toward ***RC*** and covers the product program. The EAD consists of four matrices in its full range (A_{CN_FR}, A_{FR_CM}, A_{CM_AV}, and A_{AV_RC}). Each matrix contains the maximum number of parameters from the connecting stages (e.g., A_{FR_CM} : total number of ***FR*** and total number of ***CM***). A full multiplication along all design matrices results in the overall consumption matrix A_{CN_RC} shown on the right side of Equation (11). This demand or consumption matrix, respectively, defines the minimum resource usage of a certain customer need. In accordance with Equation (10) and Figure 26 Based on this matrix, customer segments and product will be definable.

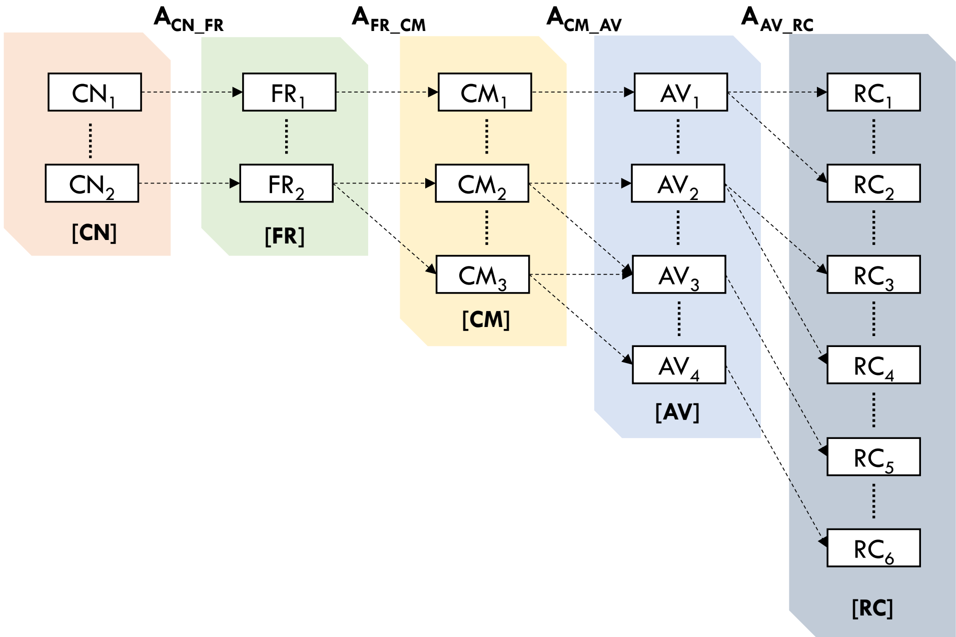

Figure 27: Illustrated EAD from customer needs (CN) up to resource demand/consumption (RC)

Matrix notation for the EAD **Resource demand/ consumption matrix**

$$\left.\begin{array}{c}
\begin{array}{cc} A_{CN_FR} & \begin{array}{cc} FR_1 & FR_2 \end{array} \\ \begin{array}{c} CN_1 \\ CN_2 \end{array} & \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \end{array} \le \\
\begin{array}{cc} A_{FR_CM} & \begin{array}{ccc} CM_1 & CM_2 & CM_3 \end{array} \\ \begin{array}{c} FR_1 \\ FR_2 \end{array} & \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \le \\
\begin{array}{cc} A_{CM_PV} & \begin{array}{cccc} AV_1 & AV_2 & AV_3 & AV_4 \end{array} \\ \begin{array}{c} CM_1 \\ CM_2 \\ CM_3 \end{array} & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 2 & 1 \end{bmatrix} \end{array} \le \\
\begin{array}{cc} A_{PV_RC} & \begin{array}{cccccc} RC_1 & RC_2 & RC_3 & RC_4 & RC_5 & RC_6 \end{array} \\ \begin{array}{c} AV_1 \\ AV_2 \\ AV_3 \\ AV_4 \end{array} & \begin{bmatrix} 1 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array}
\end{array}\right] \quad
\begin{array}{cc} A_{CN_RC} & \begin{array}{cccccc} RC_1 & RC_2 & RC_3 & RC_4 & RC_5 & RC_6 \end{array} \\ \begin{array}{c} CN_1 \\ CN_2 \end{array} & \begin{bmatrix} 1 & 2 & 2 & 1 & 1 & 0 \\ 2 & 4 & 4 & 2 & 4 & 1 \end{bmatrix} \end{array} \tag{11}$$

The EAD coins several advantages for researchers and practitioners. First, the EAD covers matrix notations (see Equation (11)) that allows mathematical experiment and investigations through simulations and optimizations, respectively. Hence, the EAD addresses questions as evaluating existent product programs, strategically planning toward new product programs or the support in computer-aided product design. Second, the framework is an accessible illustration for complex product programs, which facilitates communication to readers and decision-makers (see Figure 27). The product variety is an elusive construct of complexity through its various product designs, organizational structures, production lines, and distinct resources. The EAD encounters the challenge by requiring stringed mappings and elements in its formalism, which will cover the product program in a structured way without neglecting essential connections. Overall, the short example should be sufficient to show that the EAD formalizes product programs based on theoretical principles, which provides a general model-based approach for examining product planning from an engineering and economic perspective.

4.5.5 Product costing in the EAD

Measuring product cost necessitates modeling costing systems in an EAD. As explained in earlier sections, costing systems measure products' resource consumption weighted by their prices to trace and allocate the costs to their origin case (see Section 2.3 for detailed explanations). Therefore, the flow of costs starts from the resource demand ***RC*** - assuming that the demand was consumed – and the respective unit resource prices $\boldsymbol{\rho}$ toward final product costs ***PCB***.

Figure 28 demonstrates how a classical two-stage costing system (see Figure 12 for a recap) is embedded in the EAD.[32] As explained, financial systems first account for resource costs ***RCC***, which need further measurement and calculation to obtain product costs ***PCB***. Before receiving this information, multiplying minimum resource consumption by demand yields the total resource consumption of each product. Summing the usages of the resources leads to total input resources ***TRU*** (***RCq*** = ***TRU*** [*1 x RCs*]). Multiplying the corresponding price $\boldsymbol{\rho}$ by ***TRU*** leads to the resource cost ***RCC*** (***TRUρ*** = ***RCC***) for every cost. Next, costing systems often implicitly start by building a resource cost pool ***RCP*** from all ***RCC*** such as a specific salary and material costs of tools.[33] Thereafter, costing differentiates between direct costs ***DC*** and indirect costs ***OH***. Direct costs are traced to their products once, whereas overheads ***RCP*** have grouped into cost pools ***CP***. In the second stage, the system distributes all ***CP*** to their products by referring to the cost driver selection heuristics. Afterward, each product receives the "true" costs under the assumption of full information about the product program.

[32] In the simplest case, the EAD combines customer needs ***CN***, functional requirements ***FR***, and design parameters ***DP*** by applying identity design matrices to abstract products (Balakrishnan et al., 2011). However, these simple products are still sufficient to address cost and capacity issues.

[33] There is still ambiguity and discussion about the correct modeling (Hoozée & Hansen, 2018). For example, Balakrishnan et al. (2011) does not aggregate ***RCC*** into ***RCP***, whereas Labro and Vanhoucke (2007) do, including aggregation, specification, and random measurement errors. For the sake of simplicity, this thesis does not get into this discussion, but sees it as necessary to have ***RCP***.

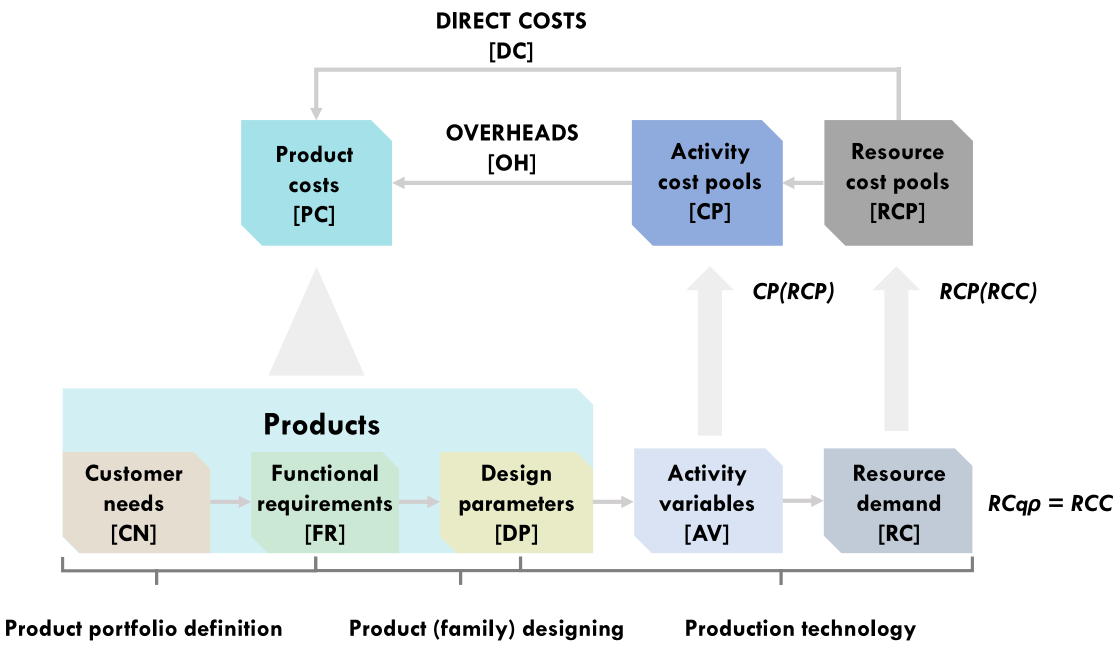

Figure 28: Product costing in the EAD

4.6 Contribution

There is a myriad of interdisciplinary questions on product-based planning processes (Balakrishnan et al., 2011; Campagnolo & Camuffo, 2010; Ravasi & Stigliani, 2012) because engineering and management still have distinct perspectives. Indeed, while both fields recognize results and continuously advance knowledge and theory, they may have unconsidered interconnections or even parallel discussions (Anderson & Dekker, 2009a; Campagnolo & Camuffo, 2010; Fixson, 2007; Simpson, 2004). For example, management accounting sees life cycle cost accounting as relevant for future research (Anand et al., 2019; Labro, 2019). Surprisingly, engineering and operations management recognized this issue in much greater detail long ago (Gu & Sosale, 1999; Krause & Gebhardt, 2018). By contrast, frameworks of service architectures (Iman, 2016; Voss & Hsuan, 2009) are prominent in management and can support starting investigations of product/service systems in engineering (Bertoni & Bertoni, 2018; Schuh et al., 2017). Overall, many overlapping research fields exist in engineering and management, and thus the EAD paves the way for common concepts by emphasizing their cohesiveness. The proposed frameworks identify at least three potential contributions to research and practice.

First, this thesis contributes to an integration of engineering design theory and economic firm theory that supplement each other and result in the EAD as an accessible and communicable framework. The EAD integrates engineering design theory through the AD and related fundamentals (Du et al., 2001; Jiao & Tseng, 2000; Suh, 1998; Ulrich, 1995; Ulrich & Eppinger, 2012) with economic firm modeling mainly promoted by the strand of the cost accounting literature (Anand et al., 2019; Christensen &

Demski, 1995). In detail, the AD's design parameters substitute the output of the economic firm, where product modeling refers to engineering theory and production technology to production theory. Cost theory finally determines the costs of all the design elements in the framework. The introduction of this integrated framework lays the platform for discussing common concepts and understandings between communities, facilitating theory development around all questions of product-based planning.

Second, the EAD does not solely connect two theories; it also overcomes the limitations of the AD and firm modeling. The AD concentrates on the optimal design of a single product (Kulak et al., 2010; Suh, 1995, 1998, 2001). Nevertheless, optimal designing is often a question of product families that go beyond the single product perspective (Eppinger & Browning, 2012; Jiao et al., 2007; Krause & Gebhardt, 2018; Simpson et al., 2014; Ulrich & Eppinger, 2012). The EAD sees $\boldsymbol{CN}$, $\boldsymbol{FR}$, and $\boldsymbol{DP}$ as the most granular units but encapsulates them into customers $\boldsymbol{C}$, products $\boldsymbol{P}$, and components $\boldsymbol{CM}$. Applying this abstraction of granularity allows the design of numerous products with one EAD that would actually require many separate AD investigations and supports estimating and modeling complex product program scenarios.

Finally, this thesis provides guidance and structure for applying the EAD to product-based planning in combination with M&S. Product-based planning, a "grand" decision process, demands a vast amount of information. Estimating scenarios and adjustments is computationally intense. Here, the EAD supports valid design structures with its theory orientation and provides a clear mapping direction at different granularities (product vs. functional requirements). This allows researchers to model existing evidence and practitioners to adapt the framework to estimate strategic scenarios under various conditions such as demand disruption. Therefore, managers and planners can test their intuition and ideas in more generalizable settings to identify robust product programs. In particular, the latter also supports system engineering and model-based engineering. Both are suitable strands for modeling complex systems such as product planning (Efatmaneshnik, Shoval, & Qiao, 2018; Eigner, Roubanov, & Zafirov, 2014; Madni, Boehm, Ghanem, Erwin, & Wheaton, 2018; Madni & Sievers, 2018; Negahban & Smith, 2014; Ramos et al., 2012), but have less common concepts and theory (Bertoni & Bertoni, 2018; Schuh et al., 2017). Hence, the EAD provides a thorough framework for testing and specifying product programs in virtual (product) laboratories, thereby addressing several communities, questions, and practices.

5. Evaluating the cost effects at modular product architectures

5.1 Introduction

Prior research has concluded that product variety increases costs (Fisher et al., 1999; Kekre & Srinivasan, 1990). However, firms are compelled to provide this variety at low costs to stay competitive, where a product modularization is a promising approach for cost-effectiveness. Many studies have identified and confirmed its cost-saving effects (Farrell & Simpson, 2009; Fixson, 2006; Jacobs et al., 2011; Jacobs et al., 2007; Kim & Chhajed, 2000; Marion et al., 2007; Pasche et al., 2011; Schuh, 1989; Siddique & Repphun, 2001; Wouters & Stadtherr, 2018; Xiong et al., 2018) as well as found that modularization reduces costs by keeping product variety high. Despite this effect, however, evidence also suggests that the cost-saving potential differs by business because of inconsistent information, overdesigning, innovation risks, module development costs, and the facilitation of copycat products (Baldwin & Henkel, 2015; Ethiraj & Levinthal, 2004; Halman, Hofer, & van Vuuren, 2003; Krishnan & Gupta, 2001). In addition, there has been less evidence about the cost-saving potential when applying modularization after Otto et al. (2016). Indeed, most of the cost-saving effects of modularization are rough estimations, intuition, or subjective opinions rather than confirmed knowledge.

This section addresses this gap in knowledge in two ways. First, it exploits large-scale product program scenarios through numerical simulations, which provide a large sample for examining the cost effects when modularizing product architectures. Numerical explorations are conventional for testing existing intuitions and causal relations in broad settings (Balakrishnan & Penno, 2014). Specifically, the field of modularization frequently applies numerical studies (Ethiraj & Levinthal, 2004; Siddique & Repphun, 2001; Sosa et al., 2004; Van den Broeke et al., 2015; Watanabe & Ane, 2004; Xu & Jiao, 2014) to identify under-discussed mechanisms from case studies and surveys.

Second, the model incorporates the guidance of Otto et al. (2016) and Meyer and Lehnerd (1997) to evaluate different platform positioning strategies. Research has intensively considered the product architecture (Fixson, 2005, 2006; Mikkola, 2007; Mikkola & Gassmann, 2003), but not explicitly accounted for market dynamics despite recommendations to the contrary (Blocher et al., 2012; Kotler & Keller, 2015; Sanchez & Mahoney, 1996). Therefore, the experiments also integrate the market perspective through product demand. By using a numerical exploration, timing is less complication. The investigation of cost-saving effects needs time to emerge (see Section 3.2) or capacity reductions are not directly observable. Finally, this section assesses existing guidance on modularization strategies and how they impact cost savings among various product program conditions.

5.2 Documentation of M&S experiments

All the experiments in this study followed a stringent documentation process to satisfy the requirements of academic rigor. There is rich guidance for maintaining academic rigor in M&S with respect to reproducibility, transparency, and generating communicable and trustable results (Barton, 2013; Grimm et al., 2010; Hinkelmann & Kempthorne, 2012; Kleijnen, 2015; Lorscheid, Heine, & Meyer, 2012; Montgomery, 2000; Siebertz et al., 2010). The forthcoming sections and experiments follow five stages: (1) constructing a conceptual model (2) classifying the dependent and independent parameters using a systematic experimental design, (3) providing descriptive statistics as an anchor for assessing the behavior of input modeling, (4) documenting the analysis and data, and (5) offering a code including its comments.

First, the conceptual model incorporates the mental model of the modeler, which is preferably aligned to the communities. Importantly, every peer needs to understand the concept to get to the heart of the assumptions and mechanisms. Many visual and textual approaches are used to build and communicate conceptual models. Some exemplify their models employing UML (Unified Modeling Language) diagrams (Bersini, 2012) and others use textual standard procedures such as the ODD (Overview, Design concepts, and Details) protocol for agent-based modeling of Grimm et al. (2010). Other valuable tools include assumption documents, as claimed by Law (2014a), and depicting the causal structure using Libby boxes (Libby, 1981; Libby et al., 2002) and structural equation models (Mertens et al., 2017). Ultimately, M&S aims to provide access to the model's assumptions and simplifications to ensure its credibility (Mårtensson & Mårtensson, 2007).

Second, computational models mainly examine the independent and dependent parameters to perform experiments. Here, a classical experimental design helps by providing substantial information about the experiment (Lorscheid et al., 2012; Montgomery, 2000; Siebertz et al., 2010). Third, the descriptive measurement of the simulation model behavior is often underestimated. Showing how inputs change the model in statistical measures may be more convincing because it parallels classical dataset analysis. Importantly, descriptive measures should also help non-peers acknowledge the impacts of input modeling on models' behavior. Specifically, Edmonds and Moss (2005) claim that complex models require more descriptive insights, and Mertens et al. (2015) provide an example that primer inputs do not necessarily explain simulation outcomes. This thesis sees it likewise and thus aims for clarity between inputs and models' behavior.

Fourth, in terms of the analysis procedure and data, Thiele, Kurth, and Grimm (2014) make their analysis procedure available to allow reviewers and later other researchers to connect and offer an alternative analysis for substantiating evidence. Finally, disclosing the code with thorough code commenting aims for academic rigor and further usage in research. Several tools are available for publishing and correctly developing and documenting codes (i.e., GitHub and R Markdown). Overall, following the guidance in M&S, this thesis aims to become as credible as possible.

5.3 Model design concept

5.3.1 Modeling modularization

Before explaining the model used, this section formalizes the modularization process used in the experiments in accordance with the product architecture. In this thesis, modularization is the process of developing and building modules and platforms. Strong couplings between components and functions can be an indicator of efficiently developing shareable modules or platforms (Baldwin & Clark, 2000; Krause & Gebhardt, 2018). Therefore, this section demonstrates and firstly formalizes modularization from an existing product architecture.

Figure 29 illustrates an existing product architecture (a) where modularization will merge functional-coupled components into a module or platform (b). One functional requirement FR_1 can branches out to three subfunctions, FR_{11}, FR_{12}, and FR_{13}. For example, this may be a heating performance of 50°C, 100°C, or 200°C, quality rating, or other tolerances. Instead of defining complex products for customers using the EAD (see Section 4.5), the modeling initially denotes three product variants consisting of four functional requirements. In sum, the figure reflects a simple product family decomposable by their existing product architecture.

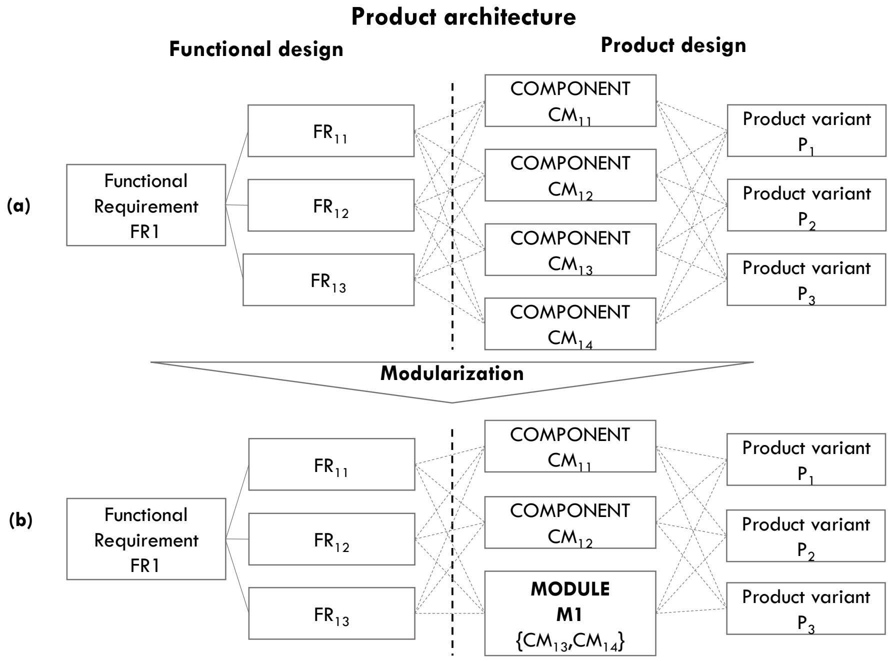

Figure 29: Formalizing modularization in the context of product architecture. The module M1 integrates CM13 and CM14

Every *FR* in a product architecture can relate to many, few, or at least one component *CM* depending on the function-component scheme (Fixson, 2006). Sharing functions among components is not arbitrary; it rather emerges from the made decisions during product-based planning manifesting in a product architecture, known as modular, integral, and mixed characteristics (see Section 2.2.3). Recall that strict pairs between one *FR* and one *CM* are modular, as indicated by one-to-one mapping. A one-to-many mapping tends to be integral, suggesting that one *FR* is related to many *CM*. More realistic scenarios contain many degrees in this contingency known as mixed architectures. Figure 29 shows the possibilities as dashed gray lines, stressing the contingency between ideal modular and integral product architectures.

Equation (12) expresses the product architecture as a design matrix in vector notation, which can be the shape of modular, mixed, and integral architectures. Modeling the product architecture parallels DMMs because there is a need to map two subsystems. Recall that the EAD sees *DP* and *CM* as a question of granularity, where sets of *DPs* result in *CM*. In the simplest case, every *DP* is one *CM*. Using this proposition, the design matrix $\boldsymbol{A_{FR\_DP}}$ of the EAD is likewise the product architecture $\boldsymbol{A_{FR\_CM}}$.

The design matrix $\boldsymbol{A_{FR\_CM}}$ models the number of functional couplings between *FRs* and *CMs* using the non-zero entries in equation (12) in accordance with the example. Having a non-zero matrix, where every function has one *CM* (modular architecture), indicates decoupled design (Suh, 2001). Continuing this progress by continuously filling the entries in the matrix will shift the design toward an integral architecture. The shifts increase integrality by enriching the couplings between *FRs* and *CMs*. When all entries are non-zero, there is ideal integrality, meaning that each function shares each *CM*.

$$[\boldsymbol{A_{FR\_CM}}] = \begin{bmatrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \end{bmatrix} \tag{12}$$

The modularization process in Figure 29 combines two components (CM_{13}, CM_{14}) into one module M_1, which binds the respective functions at one asset. The module accrues former *FRs* to ensure customer satisfaction. Because the module binds all the functions of the previous components, it is more expensive. Through the aggregation, it is necessary to adjust the subsequent design of *AV* and *RC*. This thesis uses the findings of Thyssen et al. (2006), who claim that the costs of a new module are “at least as costly as the costliest component”. For instance, integrating one cheap and one expensive component into a module reduces the probability that it costs less than the most expensive components before. Hence, the modularization will use the costliest requirements of *AV* and *RC* from the former production technology as a proxy to ensure the higher costs for the module by dropping the production lines of the less costly components. Finally, two components end up in one module with one production line and a respective set of resources. Overall, this section provides the modularization model used in the forthcoming numerical exploration.

5.3.2 Conceptual model

The conceptual model includes the product-based planning process with the EAD, which uses several parameters to generate a large set of scenarios. To detect the positive and negative cost effects of modularization, the model first generates an artificial product program consisting of an initial product architecture without any modules or platforms. Second, the model uses the previously described modularization mechanisms that aggregate the components and adjust the production technology. Lastly, the modular product program has a new economic state, including new product variant costs. The difference between the reference and modular product program allows me to assess the impact of the modularization. To sum up, Figure 30 shows the events in one round.

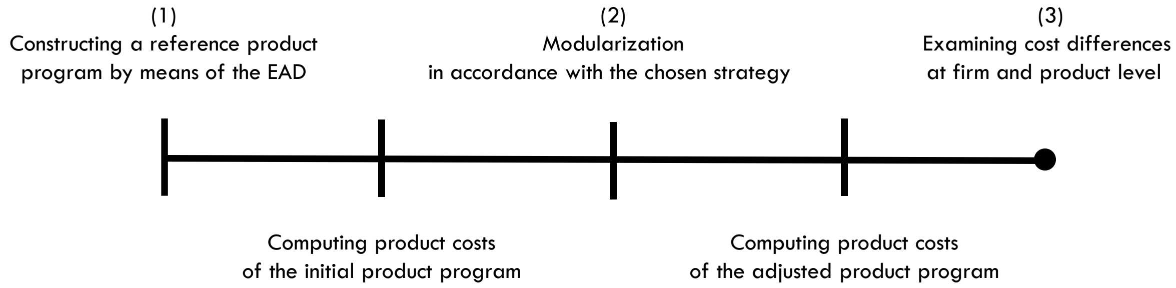

Figure 30: Conceptual walkthrough of one simulation run

Figure 30 illustrates the routine for one simulation run that compares the costs of the initial and modular product programs. The routine of the model disseminates to three subroutines. First, the implemented modeling in the EAD can provide reference product programs without any modules or platforms. This approach is far from new; indeed, referencing or constructing benchmarks is common in many disciplines (Anand et al., 2017; Ethiraj & Levinthal, 2004). Israelsen and Jørgensen (2011) adopt a similar approach in a modularization context. The model uses the market segmentation grid (see Figure 19) as actual guidance for deciding on modularization strategies (Otto et al., 2016; Simpson et al., 2011). Thus, it has a specific product program referring to an existing market segmentation grid yielding the final product and firms' costs. Second, the modularization adjusts the existing product architecture using the chosen modularization strategy (see Section 3.2.3). The selected strategy then switches the cost situation of the firm because modules will substitute components and their respective production lines. This manipulation affects the overall design of the existing product architecture as well as the previous process and resource commitments. The last level of the routine calculates the new costs after modularization under the same cost drivers to ensure a fair comparison. Assessing the cost difference shows the positive and negative cost-saving effects of the modularization.

5.3.3 Computational model

“Benchmark”

The computational model transforms the conceptual model into an executable program for performing numerical calculations. Starting with the initial product program, Figure 31 illustrates one principal design modeled by the formalism of the EAD. It starts with a product portfolio definition, including C customer segments [1 x *Cs*] that depend on the strategy referring to the market segmentation grid. Assuming a perfect product portfolio definition, three product variants *P* [1 x *Ps*] are sufficient for covering the market segment. This simplification is valid as long as there is a one-to-one mapping between ***CN*** and ***FR***. Next, customers’ ***C(CN,q)*** demand for their product variants leads to the subsequent ***CM***, ***AV***, and ***RC***.

The demand *q* of each product variant ***P***(***FR***,***q***) diffuses over the product architecture $\boldsymbol{A_{FR\_CM}}$ toward the required ***CM*** (***FRq*** = $\boldsymbol{A_{FR\_CM}}$ ***CMq***). The product architecture $\boldsymbol{A_{FR\_CM}}$ changes its fillings using *PA_DENS*. This factor regulates the sharing between ***FR*** and ***CM***, indicating how many non-zero values will be in the matrix (see equation (12) for a simple example). This computation hence decides on the initial characterization of the product architecture (modular, mixed, and integral). Recall that this is assumed to be crucial for the forthcoming modularization (Fixson, 2005, 2006).

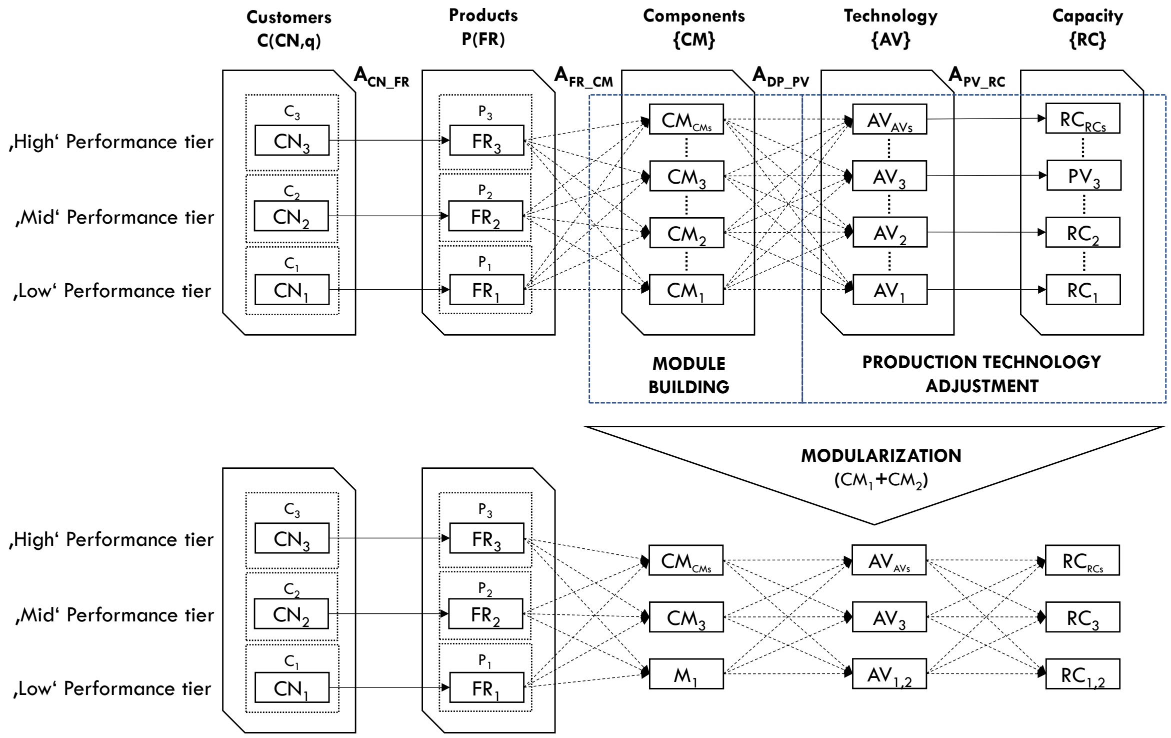

Figure 31: Conceptual product program through the EAD

Next, such demand prompts production technology to supply the necessary number of ***CM*** or module ***M***. Typical examples of a component’s production technology range from the external procurement of materials or liquids to internal services such as material movements, engineering, and maintenance activities. The computational product model randomly fills the design matrix with non-zeros parameterized by the factor *AV_DENS*. This process is identical to those of previous numerical studies (Anand et al., 2019). Finally, every *CM* requires a specific set of ***AV***, where an identity design matrix $\boldsymbol{A}_{\boldsymbol{AV\_RC}}$ directly triggers the ***RC***.

The identity matrix of $\boldsymbol{A}_{\boldsymbol{AV\_RC}}$ continues the demand pull from ***AV*** toward one ***RC***. For example, having a process requirement of 5 hours (i.e., hardening or painting) determines a minimum input requirement of 5 hours at a single resource. This condition shows similar behavior to demand. Thus, demand ***q*** yields firms' total resource consumption ***TRU*** multiplied by prices $\boldsymbol{\rho}$ to obtain ***RCC***. At this point, the costs are retractable to the product variants in the full information setting, where the initial product program is expressed through product costs.

"Modularization"

Next, modularization integrates components ***CM*** into modules ***M*** by the functional couplings in the product architecture $\boldsymbol{A}_{\boldsymbol{FR\_CM}}$. Afterward, the model pools the corresponding processes ***AV*** and resources ***RC*** from the integrated components. The modularization has full information, which is a supporting assumption otherwise new issues would arise (Ethiraj & Levinthal, 2004). Thus, the product program is entirely observable through the design sets of all the design parameters ***CN***, ***FR***, ***DP***, ***AV***, and ***RC*** and design matrices $\boldsymbol{A}_{\boldsymbol{FR\_CM}}$, $\boldsymbol{A}_{\boldsymbol{CM\_AV}}$, and $\boldsymbol{A}_{\boldsymbol{AV\_RC}}$.

The modularization follows the strategy of the market segmentation grid and the selected performance tier *OD*. Targeting the "High" performance tier (*OD*=3) with horizontal leveraging, the modularization seeks to develop modules solely in this grid. Therefore, it integrates all functional-related ***CM*** in the segments (Section 5.3.1). While this approach may not be efficient in practice, the model nevertheless provides cost savings under the given circumstances of the product program. Overall, the modularization depends on the chosen strategy of the market segmentation grid, chosen performance tier *OD* ("Low"=1, "Mid"=2, "High"=3), and conditions of the initial product program.

Finally, computational modeling provides a laboratory for constructing product programs based on the theory connecting EAD. Manipulating the product program from the lab provides responses to any design adjustments in the program. The results can disentangle and initiate discussions on the underlying causal mechanisms (i.e., modularization and adjustments) (Balakrishnan & Penno, 2014). Overall, this thesis thus proposes a product program model that can analyze economic states during change.

5.3.4 Simulation model protocol

This section describes the parameters and their variation during the experimental exploration, which are applicable to the numerous reference scenarios of the product programs. Table 4 classifies the parameters of the experiments, many of which have previously been used. For example, cost accounting studies have used *AV_DENS* and *RC_VAR* (Anand et al., 2019). Analytical and conceptual studies such as Moorthy and Png (1992) and Krishnan and Gupta (2001) have used *Q_VAR*. On the contrary, other factors are new, especially the density of the product architecture *PA_DENS*. The next paragraphs provide a detailed view of each parameter supported by the descriptive statistics in Table 5 that shed light on the behavior of the simulation model and relate the results to the empirical observations.

Table 4: Parameter and factor classification of the modularization model

Independent parameters	Control parameters	Dependent parameters
Customer demand diversity [*Q_VAR*] [-2,-1,0,1,2]	Number of customers [*NUMB_C*]	Product (variant) cost difference [%] [*ΔPC*]
Targeted tier for the module/platform [*OD*] [1,2,3]	Number of customers' needs [*NUMB_CN*]	Production (variant) cost difference [%] [*ΔPPC*]
A_{FR_DP} density/product architecture [*PA_DENS*] [0.35,0.6,0.85]	Number of functional requirements [*NUMB_FR*]	Firms' total cost difference [%] [*ΔTC*]
A_{DP_AV} density/production technology [*AV_DENS*] [0.35,0.6,0.85]	Maximum level of *FR* [*NUMB_FR_MAX*]	
Resource cost dispersion [*RC_VAR*] [0.45,0.6,0.85]	Number of resources *RC* [*NUMB_RC*]	
Unit-level process share [*UNIT_SHARE*] [0.3,0.5,0.7]	Number of activities *AV* [*NUMB_AV*]	
Number of component [*NUMB_CM*] [3,6,9,12,15,18,24]	Simulation repetitions [*n*]	
	Firms' initial total costs [*TC*]	
	Total demand [*TQ*]	
Identity design matrices of A_{CN_FR}=1; A_{AV_RC}=1		

The first independent factor is *Q_VAR* that disseminates a total demand of *TQ*=100 to all customer segments. While having different performance tiers, as Figure 31 shows whether the "High" or "Low" customer segment has substantial demand differs. The simulation hence uses negative values (i.e., -2) to model "High" with the lowest demand (~6.2%). For positive values of *Q_VAR* (i.e., 2), "High" has the highest demand (~73%) in terms of *TQ*. Following previous studies, this thesis includes a measure called "market diversity" or "cannibalization" *R* (see Equation (13)). This measure has been used in analytical studies to explain the link from market diversity to demand (Krishnan & Gupta, 2001; Moorthy & Png, 1992). Equation (13) shows the calculation, where demand for "High" relates to that for "Low". As a result, the market is diverse when having significant demand for "High" performance product variants in contrast to "Low" product variants in the same family. Ideally, the equation would use product value; nonetheless, based on previous analytical studies (Mussa & Rosen, 1978), costs can be linear to performance and utility, where costs are a valid proxy. As expected, the descriptive statistics in Table 5 demonstrate that *Q_VAR* drives market diversity to a large extent.

$$R = \frac{q_H}{q_L}\left(\frac{pc_H - pc_L}{pc_L}\right) \tag{13}$$

The next factor *OD* embodies the design target in the performance tier, where *OD*=1 ("Low") constructs modules in the "Low" performance segment, followed by *OD*=2 and *OD*=3 analogously. In the following example, each of the product variants has only one component. Building a module at the "Mid" level (*OD*=2) combines two components into a new module. Increasing the components in several tiers, modules, and platforms can become more extensive. This process logically continues with *OD*=2 ("Mid") and *OD*=3 ("High") in the same manner.

The factor *PA_DENS* defines the product (family) architecture that incorporates the probability of mappings between ***FR*** and ***CM***. For instance, having a large *PA_DENS* (~0.8), functions have more linkages with more components, indicating integrality. Analogously, lower values (~0.2) imply fewer mappings and a more modular architecture (Hölttä-Otto & de Weck, 2007; Ulrich, 1995). This factor is therefore responsible for modeling integral, mixed, and modular product architectures.[34]

AV_DENS regulates the sharing of processes and resources among components. This factor has been extracted from previous numerical studies in cost accounting (Balakrishnan et al., 2011) and has a tremendous impact on the diversity of production technology and resource consumption. For instance, having high *AV_DENS* (0.85), one component uses many processes (~17), somehow highlighting mass or simple production processing. Analogously. a low *AV_DENS* (0.35) leads to a job shop environment, namely having distributed workshops for specific products due to the lack of sharing among machines and processes (~7).

RC_VAR determines the diversity of resource cost drivers following previous research (Balakrishnan et al., 2011). This factor regulates the dispersion between expensive and cheap resource costs in a production environment. For instance, *RC_VAR* (1.5) surrogates a diversified resource cost structure, meaning that few resources are costly and others remain low. Conversely, a low value of 0.5 indicates the opposite and reflects a uniform cost distribution.

The number of components *CMs* relies, on the one hand, on empirical studies (Hölttä-Otto & de Weck, 2007) and, on the other, on analytical ones (Moon & Simpson, 2014). Every component in the model is an entity that affects the production technology by a set of processes and resources. Larger modules can incorporate more scaling effects such as fixed cost degression because more components proportionally increase efficacy.

There are more possible parameters; however, reducing numerical complexity is a severe challenge to computational efforts. Not controlling for dimensional parameters can result in an exponential growth in complexity, raising computational effort without knowing whether it enhances the value of the likely findings. Therefore, limiting parameters to the research problem is necessary. Accordingly, some parameters can reduce the hierarchical structures and dimensions of the domains (i.e., *NUMB_FR_MAX* and *AVs*), where identity designs decouple all the relations between domains (i.e., A_{CN_FR}=1; A_{AV_RC}=1). The costs are fixed for every initial product program at TC = 10,000€, where 30–50% are randomly chosen as non-unit costs (Anand et al., 2019; Balakrishnan et al., 2011). Cost structure theory is therefore traditional (i.e., including variable and fixed costs). Lastly, the dependent variables are relative measures of cost changes to assess the impact of the modularization. The first dependent parameter *ΔPC* concerns

[34] As there is the reasonable minimum requirement that each functional requirement has at least one component, an exception handler automatically correct it. As a result, the adjusted parameter of PA_DENS (i.e., 0.2) are not necessarily exact 20% of the total possible linkages.

each product variant. The measure consists of the difference between the product costs of the adjusted firm after modularization ***PCM*** and those of the reference ***PCB*** ($\Delta PC = (PCM - PCB)/PCB$). A similar measure is ΔPPC, which uses only variable costs for the calculation to provide manufacturing cost information. The central measure of the experiments is ΔTC, which focuses on changes in firms' total costs between the initial TC and after modularization TCM ($\Delta TC = (TCM - TC)/TC$).

Table 5: Descriptive statistics about the benchmark product programs

			Average values				
Customer demand diversity (*Q_VAR*)	Unit	Global Average	Low demand for “High” product variant (*Q_VAR* = -2)	(*Q_VAR* = -1)	Equal demand between all product variants (*Q_VAR* =0)	(*Q_VAR* = 1)	Large demand for “High” product variant (*Q_VAR* = 2)
Relative percentage of the “High” product demand	[%]	**37.17**	6.22	13.42	33.33	59.20	73.64
Market diversity of Moorthy and Png (1992)	#	**741.65**	35.95	53.50	123.06	655.15	2,840
Relative percentage of the costs of the “High” product	[%]	**43.00**	24.80	29.93	42.19	55.51	62.76
Density of the product family architecture (*PA_DENS*)		Global Average	Modular architecture (*PA_DENS* = 0.35)		Mixed architecture (PA_*DENS* = 0.6)		Integral architecture (PA_*DENS* = 0.85)
Percentage of zero entries in the product architecture	[%]	**43.51**	37.40		43.50		49.62
Percentage of costs in the “High” product	[%]	**43.3**	38.88		43.33		47.58
Density of the process consumption (*AV_DENS*)		Global Average	Little sharing of resources (*AV_DENS* = 0.35)		Medium sharing of resources (AV_*DENS* = 0.6)		High sharing of resources (AV_*DENS* = 0.85)
Percentage of zero entries in the consumption matrix	[%]	**40.81**	62.58		41.55		18.31
Average process usage of activities of the component (max.=20)	#	**11.83**	7.48		11.68		16.34
Average range of process consumption across products	[%]	**66.90**	80.68		65.72		53.70
Number of components (*CM*)		Global Average	Analytical component setting (*NUMB_CM* = 3)		Moderate components (*NUMB_CM* = 6)		Many components (*NUMB_CM* = 9)
Relative percentage of the costs of the “High” product	[%]	**43.30**	48.63		41.10		39.29
Cost share of the 20% costliest components compared with the total initial costs (descriptive value *COSTHIGH*)	[%]	**54.31**	58.66		59.06		45.20

[1] n=121,500

[2] The value *COSTHIGH* is used later to measure the dispersion among the component costs

5.4 Investigating the cost effects of modularization

5.4.1 Examining the cost effects of vertical leveraging

The first experiment concerns the investigation of the cost effects of vertical leveraging without *parametric scaling*. The first experiment is limited to upscales in terms of platforms and modules to examine the overdesign costs at a lower performance tier when designing modules or platforms for higher performance tiers. Figure 32 illustrates the market segmentation grid presented by Meyer and Lehnerd (1997) with the implemented strategy of vertical leveraging. Importantly, the experiment accounts for vertical leveraging in its 'true' meaning, whereby the same platform or component is used among different performance tiers. This prevents the ability to scale, where overdesigns are obligatory (Kipp, 2012; Krause & Gebhardt, 2018). Hence, the first experiment uses one market segment and applies modularization at each performance tier through including overdesign *OD*. Table 6 explicates the experimental design further.

Before discussing results, the next paragraph disentangles the difference between vertical scaling and leveraging. Meyer and Lehnerd (1997) primarily defined "vertical platform scaling" (see Section 3.2.3) as a strategy to adjust functionalities of existent platforms from "High" ("Low") to "Low" ("High") performance tiers through adjusting size, weight, length or functionalities. Interestingly, current research do not use "vertical scaling" but rather "vertical leveraging" (Hölttä-Otto, 2005; Otto et al., 2016; Ramdas, 2003; Siddique & Repphun, 2001; Simpson, 2004; Simpson et al., 2011; Simpson, Maier, & Mistree, 2001) and continuously cite Meyer and Lehnerd (1997) even though they have not proposed this strategy.

While scaling involves design changes through more components, leveraging does not allow adjustments and lead to overdesign. It may be hair-splitting to mention an artifact in wording but leveraging and scaling platforms or components are different design activities concerning Meyer and Lehnerd (1997). Both leveraging and scaling will cover for more than one segment or performance tier, however, their underlying design implications are distinct. While scaling allows for unlimited design adjustments and firms only leverage their knowledge to develop specific platforms faster and more cost-efficient (Meyer & Lehnerd, 1997, pp. 58-60), leveraging means that the identical platform or component is used for several segments or tiers. Specifically, 'physically' vertical leveraging underlies the effect of overdesign whereas scaling does not. In sum, this thesis concludes a distinctiveness between *leveraging* and *scaling* between performance tiers .

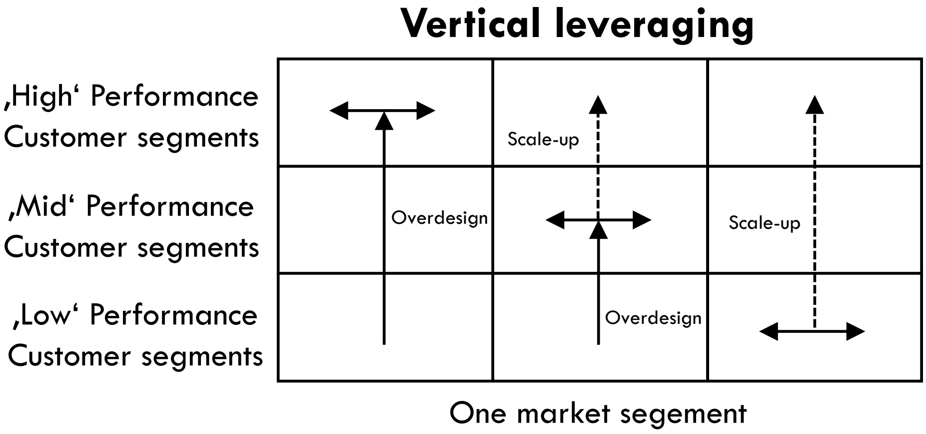

Figure 32: Vertical leveraging with overdesign

Table 6: Experimental design – Vertical leveraging experiment

Independent parameters		Control parameters		Dependent parameters
OD	[Low, Mid, High]	Processes	20	Product (variant) cost difference
Q_VAR	[-2,-1,0,1,2]	Resources	20	[%] [ΔPC]
AV_DENS	[0.35,0.5,0.85]	Products/Customers	3	Production (variant) cost difference
PA_DENS	[0,0.2,0.4,0.6,0.8,1]	Repetitions	50	[%] [ΔPPC]
UNIT_SHARE	[0.3,0.5,0.7]	Initial total costs	10^4	Firms' total cost difference
RC_VAR	[0.5,RND,2]	Total demand in the segment	100	[%] [ΔTC]
NUMB_CM	[3]			
n= 40,500 (5 · 3 · 6 · 3 · 3 · 50)				

Equation (14) demonstrates a constrained product architecture for satisfying the condition of increasing performance, costs, and quality in the tiers (the association has been considered in Section 2.2). Using a full matrix – as explained in the formalization – allows for mixed designs, meaning that FR_{13} can have higher or lower costs than FR_{11}. The experiment needs to prevent those conditions by setting zeros in the upper triangle of the product architecture $\boldsymbol{A_{FR\_CM}}$. Describing the design matrix further, A_{11} is a one-to-one mapping between the subfunction FR_{11} and component CM_1, where function FR_{12} has two *CM*, advocating a mixed architecture. Importantly, it also contains CM_1, where FR_{12} is based on the previous function but extends it somehow. FR_{13} is connected to all *CM* and reflects a more integral function. Thus, each *FR* accumulates *CM* and the corresponding costs. The increase of costs by quality and performance in a common analytical assumption (Section 2.2.2), where the experiment uses the constrained triangular product architecture to satisfy.[35]

$$[\boldsymbol{A_{FR\_DP}}] = \begin{bmatrix} A_{11} & 0 & 0 \\ A_{21} & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{bmatrix} \tag{14}$$

Both panels of Figure 33 report that vertical leveraging is less cost-effective for firms because cost increases are more likely. At *Q_VAR*=-2, there is less demand (i.e., 6 units from 100), where *Q_VAR*=2 indicates larger demand for the "High" product variant (i.e., 73 units from 100). At negative levels of

[35] This thesis tested several types of constrained product architectures including full and several partial matrix designs. Interestingly, there was less difference than expected but the proposed scenario may be the most intuitive.

Q_VAR, the platform strategies "High" (*OD*=3) and "Mid" (*OD*=2) increase firms' total costs enormously on average (~750%, ~180%). This is intuitive as both strategies overdesign the large demanded "Low" and "Mid" product variant. By contrast, the "Low" platform shows no savings because there is no modularization owing to the analytical number of components (*NUMB_CM*=3). Interestingly, the total cost increase behaves exponentially, where *OD*=3 may increase due to doubled overdesign effects at the "Low" and "Mid" product variants. Hence, the cost-saving effects when overdesigning are not straightforward, in line with Krishnan and Gupta (2001).

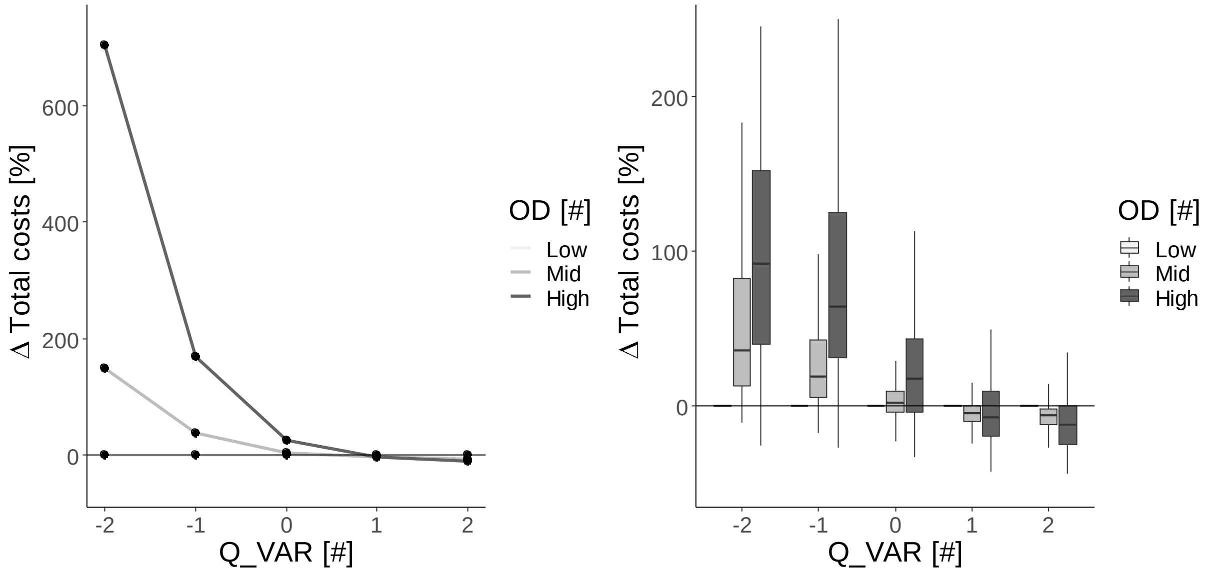

Figure 33: Total cost effects of vertical leveraging under varying demand; Panel A (left): Estimated mean plot; Panel B (right): Boxplots

The right panel of Figure 33 indicates the profitable areas of vertical leveraging, particularly when facing large demand at the respective performance tier. The greater demand for the "High" product variant, the greater the potential for cost savings for the firm, as the modularization develops a large platform leveraging a standardization that can profit significantly from economies of scale. Interestingly, the total costs decrease does not strictly corroborate previous findings (Krishnan & Gupta, 2001). Thus, rising demand for the chosen segments for modularization favors the cost-saving effects because overdesign costs of other segments are reduced.[36]

Concerning the product architecture in Figure 34, integrality proposes cost-saving and cost-increasing effects. Recall that *PA_DENS*=0 means a perfect modular architecture, where *PA_DENS*=1 is perfect integral. The boxplot panel highlights that large integrality has significant variance in terms of total cost decreases and increases. Increasing integrality may incur overdesign costs as well as cost-saving effects through economies of scale. This ambivalent behavior may be an interaction effect when demand is high. Further, the cost-saving effects of *PA_DENS* are not fully explainable, suggesting that the vertical leveraging of integral product architectures offers opportunities and risks.

[36] Figure 33 also documents the 'low' performance segment but it is entirely at zero. This comes as no surprise, because the experiment is restricted to three components (*NUMB_CM=3*).

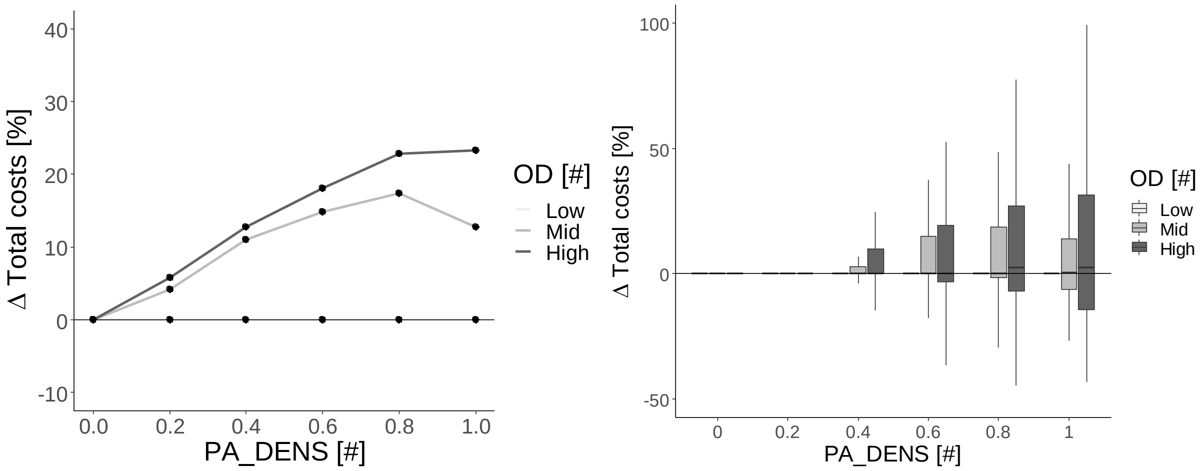

Figure 34: Total cost effects of vertical leveraging under the density of the product architecture; Panel A (left): Estimated mean plot; Panel B (right): Boxplots

Before disentangling the drivers behind the cost savings of *PA_DENS*, Figure 35 shows the product perspective of the product and production variant costs in the considered market grid. The first row depicts the full product costs and the lower row only production costs. These rows have qualitative differences. The vertical leveraging of the "High" performance tier (*OD*=3) at *Q_VAR*=-2 reduces "High" product variant costs (~17%). This observation explains a transition from existing economies of scale from the "Mid" and "Low" at the "High" product variant. However, this advantage comes in exchange for the increasing costs for the "Low" and "Mid" variants. Hence, overdesigning costs affect the whole product family, which are responsible for firms' total cost increase.

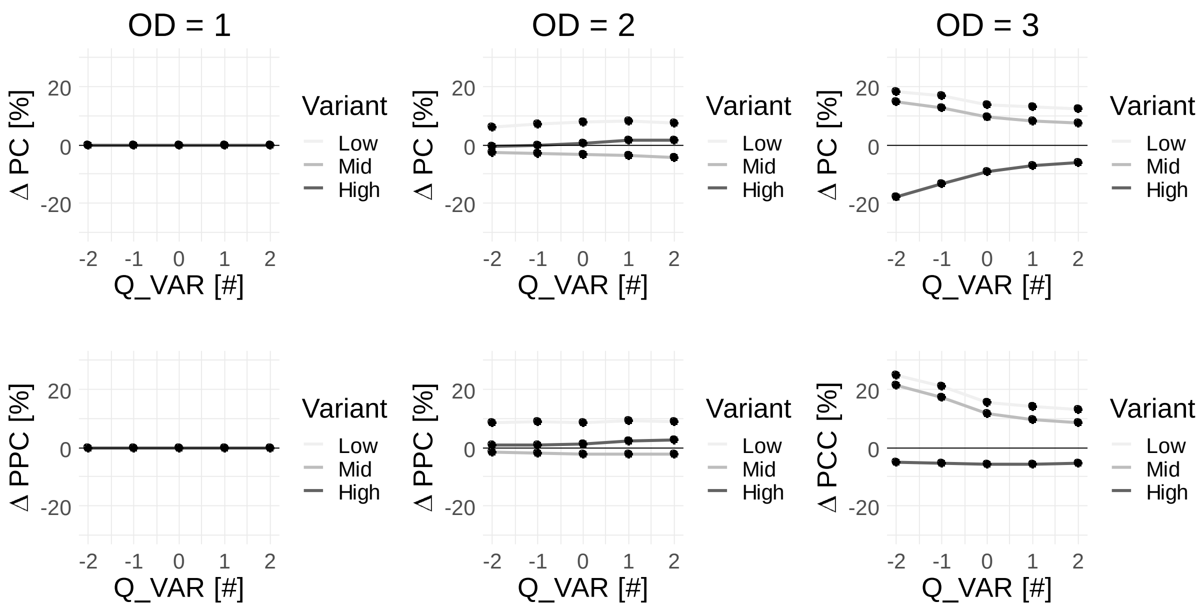

Figure 35: Estimated mean plots of the product cost when applying vertical leveraging

Another finding from Figure 35 is that the variants have economies of scale in terms of lower production costs. At *OD*=3 the "High" product receives production variant cost reductions of ~5% on average, where "Mid" and "Low" have increases of ~10% on average. This suggests that vertical leveraging leads to larger cost increases; nonetheless, this could be a false conclusion because total costs are not anticipatable from single product cost information. As a result, this thesis stresses that estimating the cost-saving effects of modularization is affected by the whole product family design.

Lastly, Figure 35 underlines the importance of market expectations for long-term forecasts. As stated, single product cost information cannot estimate general cost consequences. Nevertheless, combining estimated product cost savings with market expectations may be worthwhile for estimating cost reductions. Hence, demand expectations and uncertainties are crucial for planning modularizations and introducing the unexplored potential of cost savings.

To sum up, vertical leveraging without parametric scaling was the foundation of the experiment because it provides the opportunity to examine overdesigning through modularization. The numerical results – likely overcoming single cases – show the following remarkable pattern: vertical leveraging best suits the chosen modularized performance tier in terms of costs, related cost effects are primarily beyond manufacturing costs as well as demand expectation are decisive. Similarly, integral product architecture is seemingly ambivalent and depends on more parameters. Overall, vertical leveraging thus encourages the sharing of economies of scale at the product level, where market expectations may be decisive for profitability.

5.4.2 Cost drivers of vertical leveraging

The regression analysis in Table 7 shows the underlying drivers of the previous results. Using an ordinary least squares regression as a metamodel can substantiate or clarify the simulation model behavior (Mertens et al., 2015). The resulting statistical model may offer more detailed explanations through effect sizes and interactions, supporting the clarity of the underlying mechanisms of vertical leveraging. In doing so, metamodels become vital for qualitative interpretations, and this thesis applies statistical measures such as standardized regression coefficients (B), effect size in a linear model (η^2), and F-values (F).

Consider Table 7, where *Q_VAR* increases total costs at larger output quantities (B=-0.54, η^2=0.07, F-value=3,354). This observation indicates that a large number of outputs at the “Low” performance tier (Q_VAR=-2) decreases total costs, whereas at “High” (Q_VAR=2) total increases. This effect is intuitive, because “High” product variants are more expensive, but it also substantiates the intended simulation model behavior.

COSTHIGH reflects the initial cost share of the “High” product variant, indicating the extent to which component costs are skewed in the reference product program. The regression model indicates a cost-saving effect (B=-0.39, η^2=0.01, F-value=852). This is interesting because it contrast previous simulation and empirical observations of (Park & Simpson, 2005); Park and Simpson (2008); Thyssen et al. (2006), who state that similar unit-level costs among unique components are a more profitable scenario for modularization. The reported experiment has an opposite effect that may refer to the missing differentiation between unit- and non-unit-level costs or to vertical leveraging. In this line, larger dispersions of component costs may be associated with more considerable savings of non-unit-level costs because expensive components can have high costs at low quantity (Cooper & Kaplan, 1987). Hence, skewed components' unit costs are assumed to be relevant indicators in selecting components for compositing modules when overdesigning.

Table 7: Regression results of the vertical leveraging experiment

TOTAL COST DIFFERENCE [%]			
	B	**η²**	**F-Value**
Q_VAR	0.54	*0.07*	3,354
OD	-0.23	*0.07*	2,590
COSTHIGH	-0.39	*0.01*	852
PA_DENS	-0.32	*0.06*	1,888
AV_DENS	0.06	*0.01*	430
Q_VAR x OD	-0.29	*0.07*	3,172
Q_VAR x PA_DENS	-[1]	-[1]	-[1]
OD x COSTHIGH	0.00	*0.01*	801
OD x PA_DENS	0.89	*0.04*	1,695
OD x AV_DENS	-0.42	*0.01*	370
PA_DENS x AV_DENS	-1.50	*0.01*	287
n		39,007	
Adj. R^2		0.33	

Multicollinearity VIF Controlled≤1 in the main effects.
The model and its coefficients are significant $p<0.05$
B = Standardized Regression Coefficients, η^2 = Effect sizes F = F-value from an ANOVA model Type III;
Less intense interaction effects in terms of $\eta^2<0.01$ are excluded.
Outliners are eliminated at a threshold >300% (n=40,500 -> n=39,007). This facilitates the normal distribution of the dependent variable for estimating the main effects.
[1] The interaction effect is overestimated (-6.45≤-1) regarding multicollinearity issues.

PA_DENS reduces firms' total costs (B=-0.32, η^2=0.06, F-value=1,888) and suggests that the integrality of the product architecture has a cost-saving effect when applying vertical leveraging. Full integrality ideally means that every component shares and has a link to every function (i.e., sometimes referred to as a bus) (Hölttä-Otto & de Weck, 2007; Ulrich, 1995) and the other way around. This should prevent overdesign costs to a large extent. Thus, the main effects may explain the unexplained cost savings of Figure 34. Consequently, this thesis concludes that integral product architectures naturally induce a high probability of cost-effectiveness.

A related strong interaction is *OD* x *PA_DENS* (B=0.89, η^2=0.04, F-value= 1,695) that demonstrates a cost-increasing effect for overdesign. Overdesigning is most likely to lead to cost increases, specifically for lower performance variants. Explaining the interaction in detail means that larger overdesigning in integral product architectures is positively associated with total cost increases. However, acknowledging interaction effects with demand, overdesign can change the outcome to positive effects, too. Consider the interaction *Q_VAR* x *OD* (B=-0.29, η^2=0.07, F-value= 3,172), which leads to the assumption that larger demand and overdesign reduce firms' total costs. In addition, *Q_VAR* x *PA_DENS* (η²=0.04, F-value=2,293) is another supportive cost-saving effect. To sum up, "High" product variants under high integrality and high demand, overdesign will save costs.

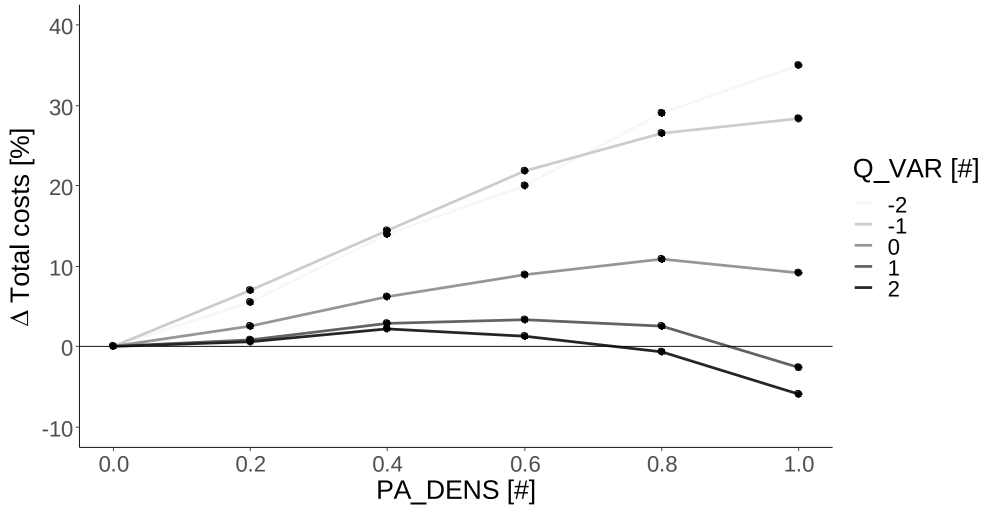

Figure 36: Demonstrating the interaction of *PA_DENS* and *Q_VAR*

Illustrating overestimated regression coefficients in the data reveals their nature. Figure 36 demonstrates that large integrality – designed as *PA_DENS*=1 – has a positive (negative) cost-saving effect at high (low) demand at the high performance tier. These results explain the boxplots of Figure 34 in greater detail and crystalize that high demand at the "High" performance variant (*Q_VAR*=2) will guarantee cost savings. Large demand (*Q_VAR*=-2) at the "Low" tier, contrarily, does the opposite probably because any overdesign will lead to higher costs for that variant.

5.4.3 Examining the cost effects of horizontal leveraging

The next experiment reports the cost effects when developing modules over market segments at three performance tiers, called as horizontal leveraging. The experiment departs from the previous one because it modularizes components in-between and between product families. Otto et al. (2016) see this strategy as comparable to swappable modules, where Figure 37 depicts the selected strategy concerning the market segmentation grid. This time, the grid comprises three market segments with three product families. This results in nine customer segments and product variants. The experimental design in Table 25 lists the used factors, which are comparable to the previous experiment.

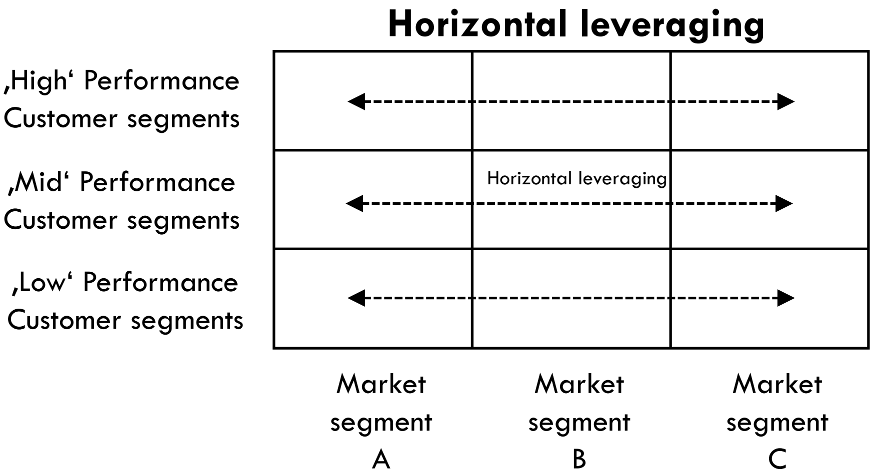

Figure 37: Horizontal leveraging

Figure 38 shows that realized demand *Q_VAR* has less impact on modularizations for horizontal leveraging. This result may sound counterintuitive but is explainable through the experimental design. In the experiment, the performance tiers share similar demand levels over product families because *Q_VAR* still disseminates demand across the performance tiers. Thus, there are no substantial demand differences at a horizontal performance tier. This condition controls for interactions in demand. Hence, there must be a substantial demand difference between components before modules can disseminate economies of scale.

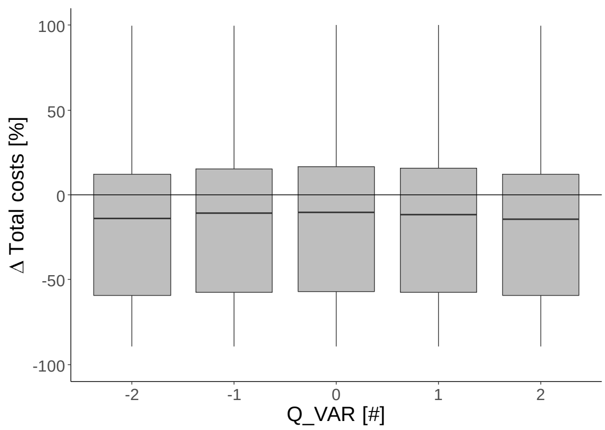

Figure 38: Total cost effects of module building along *Q_VAR*

It is striking from Figure 39 (both panels) that the density of the product architectures *PA_DENS* has a non-linear cost-saving effect. As stated earlier, questions remain about the cost effects when applying modularization. Evidence of the relation between product architectures and costs is inconclusive and rarely discussed quantitatively. The data of the experiment show that modularizing from a more modular product architecture tends to increase firms' total costs. Increasing integrality continuously alters the setting to a cost-saving scenario, but not linear. A potential explanation may be that modular architectures have more function-specific than function-sharing components. When then applying modularization, there is a higher probability of integrating function-specific components into a module or platform. Therefore, the contingency between modular and integral product architectures has a non-linear cost-saving effect when modularizing.

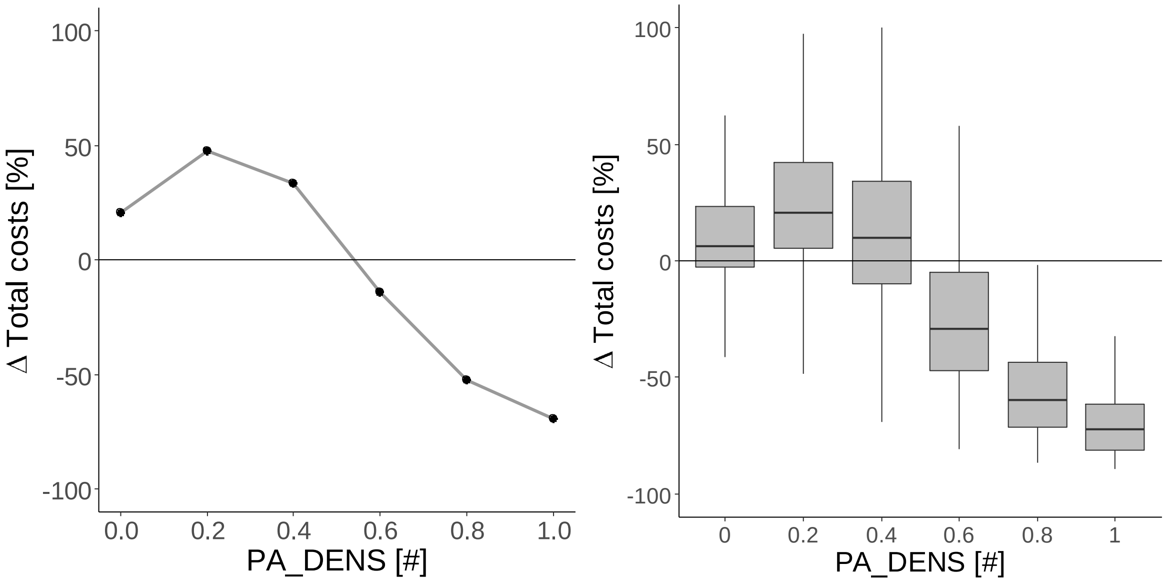

Figure 39: Total cost effects of module building;
Panel A (left): Estimated mean plot; Panel B (right): Boxplots

Disentangling the cost-saving effect of the product architecture further, Figure 40 highlights the importance of the number of components (*NUMB_CM*) and components' cost dispersion (*COSTHIGH*). The left panel of Figure 40 shows the potential cost savings when modules and platforms integrate more components. As a result, the cost-saving effect is proportional to the integrated components of a module or platform. The right panel shows the impact of a skewed cost dispersion among components that tends to weaken the cost-saving effects. This time, the data extends the result of Thyssen et al. (2006) because the horizontal leveraging is seemingly more profitable when costs, including product-sustaining and batch-level costs, have fewer differences.

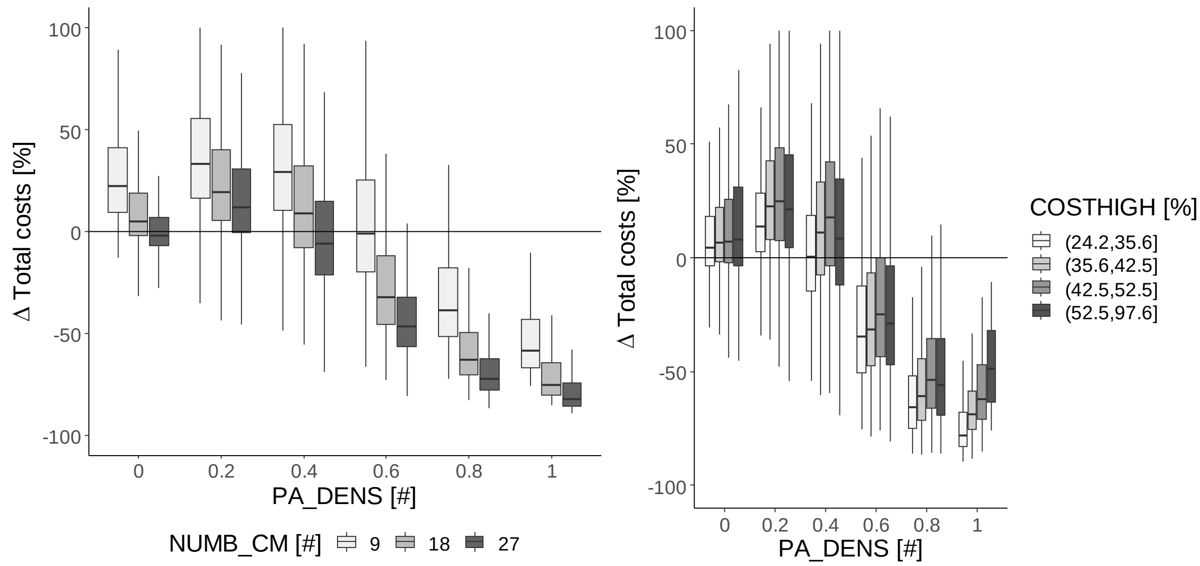

Figure 40: Total cost effects of module building considering the costs of components
Panel A (left): Box plot *NUMB_CM*; Panel B (right): Box plot *COSTHIGH*

Overall, applying horizontal leveraging as part of the modularization strategy often has large cost-saving potential. One remarkable result is that the integrality of a product architecture is a measurable driver for estimating cost savings when modularizing. The experiment demonstrates that product architectures' contingency between initial modularity and integrality has non-linear cost behavior. The more modular a product architecture, the more likely are function-specific components. Using function-specific components for modules generally increases the probability of unintended overdesign costs. Specifically, components with some function sharing tend to increase costs. This pattern highlights that large functional-sharing components have higher opportunities for cost savings when integrating them into modules or platforms. Another observation concerns the number of components, which is likely to emphasize the cost-saving effects from reducing the existing production technology.

5.4.4 Cost drivers of horizontal leveraging

As the last step in the horizontal leveraging experiment, a metamodel supports the evaluation of the driving effects using a statistical regression model. Table 8 shows an R^2 of 0.59, which indicates plausible prediction capabilities in using an almost linear model, where only one interaction effect is significant. As the data demonstrate, there are fewer areas for cost increases than decreases, where *PA_DENS* is the most potent cost driver for cost savings (B=-0.68, η^2=0.51, F-value=1,888), as in Figure 39 and Figure 40. Hence, this thesis can statistically substantiate that the characteristics of a product architecture are decisive for anticipating the potential cost effects under modularization.

Surprisingly, *AV_DENS* (B=-0.28, η^2=0.17, F-value=430) has a critical cost-reducing effect, too. This was unexpected because modularization is known to reduce complexity or especially supports complexity management (Lai & Gershenson, 2007). The regression model instead highlights that when the production technology has less diversity (i.e., more sharing of resources as in mass production), more substantial cost savings are possible. Thus, this thesis suggests that module building is more cost-efficient under both less complexity and more (process) commonality.

COSTHIGH has the opposite effect to the experiment before (B=0.08, η^2=0.02, F-value=852). Again, Thyssen et al. (2006) claim that skewed unique components yield more expensive modules and probably higher costs in total. Thus, this thesis could add evidence to the empirical finding that skewed component costs can increase total costs through more costly modules.

Table 8: Regression results of the module experiment

	TOTAL COST DIFFERENCE [%]		
	B	**η^2**	**F-Value**
Q_VAR	0.00		3,354
COSTHIGH	0.08	*0.02*	852
PA_DENS	-0.68	*0.51*	1,888
AV_DENS	-0.28	*0.17*	430
UNIT_SHARE	0.01		26
COSTHIGH x AV_DENS	-0.04	*0.01*	128
n		121,499[1]	
R^2-adj		0.59	

Multicollinearity VIF Controlled≤1
The model and all shown effects are significant $p<0.05$
B = Standardized regression coefficients, η^2 = Effect sizes F = F-value from an ANOVA model Type III;
Less intense interaction effects in terms of $\eta^2<0.01$ are excluded.
[1]One observation was corrupted regarding the factor building of *COSTHIGH*

Q_VAR and *UNIT_SHARE* have no effects to consider in the regression model. Surprisingly, there is only one significant interaction effect, namely *COSTHIGH* x *AV_DENS*. This suggests that the skewness in the component costs is less cost increasing in a less diverse production environment. This may be plausible because the new platforms or modules may already benefit from sharing existing resources. Overall, this thesis concludes that less diverse production environments that have high resource sharing are more profitable scenarios for modularization.

5.5 Contribution

Extending product programs using new product variants increases sales but does not necessarily increase profit because the associated variety comes with higher costs (Kekre & Srinivasan, 1990). To prevent this creeping progress, modularization may be a fruitful approach for achieving cost-effectiveness (Wouters & Morales, 2014; Wouters et al., 2016; Wouters & Stadtherr, 2018). Unfortunately, generalizable guidance for anticipating potential profitability when modularizing product architectures is lacking (Fixson, 2005, 2006; Park & Simpson, 2005; Park & Simpson, 2008; Thyssen et al., 2006). This thesis overcomes this limitation through a deductive model-based engineering analysis of modularization by employing the EAD. This model uses M&S to examine the cost-saving effects among various product program conditions from customers to resources. In doing so, this section describes four contributions.

First, this thesis disentangles the mechanisms of vertical and horizontal leveraging during modularization and offers new practical insights and guidance. Considering vertical levels, it suggests a precise differentiation between vertical scaling and leveraging. While *scaling* allows unrestricted adjustments over the performance tiers in terms of size, weight, quality, and components, this thesis argues that *leveraging* prevents this possibility. As a result, vertical leveraging will *overdesign* modules while overspecifying product variants at the lower performance tiers.

Second, the thesis identifies a non-linear cost-saving effect of horizontal leveraging when product architectures' integrality increases. This thesis agrees with previous research (Fixson, 2005, 2006; Park & Simpson, 2008) that integral product architectures have larger function-sharing components. However, there has been no clear evidence of how the product architecture affects costs on average. This thesis finds the unexpected effect that composing components with less function-sharing to modules and platforms tend to increase firms' costs. This effect only diminishes when using large function-sharing components. To explain this phenomenon, this thesis suggests that unintended overdesign costs frequently appear when using less function-sharing components in constructing modules. These kinds of components increases the probability that modules contain unnecessary functionalities for several variants. This mechanism diminishes at higher levels of integrality. Overall, this thesis recommends first to composite high function-sharing components into modules and platforms to achieve the highest cost savings and second that integral product architectures are particularly worthwhile for modularizations.

Third, this thesis shows that the cost-saving effects of modularization take place at the firm level rather than at the product level. Although the results document that single product variants frequently increase in costs, it does not affect total cost-savings of firms. While the responsibility for costs mainly falls to departments, teams or projects (Horngren et al., 2014), clear tracing of cost-savings from modularization may be hampered. This ambiguity hampers empirical observations of cost savings, particularly when considering non-unit costs such as fixed salaries, annual machine depreciation, or releasing capacities.

Lastly, this thesis demonstrates that less complexity in the production technology increases the potential for cost-saving. This thesis finds that less complexity (e.g., process commonality) provides higher cost-saving potentials referring to easier sharing of resources. Although modularization is seemingly a tool to manage complexity (Ehrlenspiel et al., 2014; Guenov, 2002; MacDuffie et al., 1996; Mikkola, 2007; Mikkola & Gassmann, 2003), it does not guarantee cost-saving potentials. This is probably due to that less complexity in the production is associated with larger sharing of processes that probably lower the efforts in changes when modularizing.

6. Simple and complex product costing

6.1 Introduction

This section has three parts. The first part **[1]** evaluates the accuracy of simple volume-based (i.e., predominantly single cost driver) costing systems in varying production environments and compares them with more complex ones. The next section **[2]** is devoted to the horserace of simpler TVC and more complex ABC systems under distinct cost structure theories. Finally **[3]**, this thesis considers a systematical increase in the direct costs of costing systems and examines how this impacts the accuracy of cost information. This experiment allows me to forecast how information technology may affect the issue of classical cost allocation.

First, the choice of cost system design is crucial for the quality of cost information but is still not fully disentangled. Empirical studies have not conclusively found evidence of when and how a specific cost design is more efficient than another. Further, some firms have improved their performance using ABC systems, whereas others have not (Cagwin & Bouwman, 2002; Kennedy & Affleck-Graves, 2001). Although ABC advocates claim that such systems have superior accuracy, this instrument lacks diffusion across all industries (Gosselin, 2006; Jones & Dugdale, 2002). Therefore, many cost system designs are still rather simple (Al-Omiri & Drury, 2007; Drury & Tayles, 2005; Schoute, 2009). Unfortunately, investigations and guidance for simple costing are limited, perhaps because TVC systems are similar to ABC ones. To investigate this implicit knowledge, the first subsection evaluates and compares simple TVC systems.

The second part of this section concerns the horserace between simple TVC and complex ABC systems under distinct cost structure theory. Complex costing systems are particularly relevant under high batch- and product-level costs (Abernethy et al., 2001; Schoute, 2011). Specifically, ABC systems address the relation between batch- and product-level activity measures and their resource consumption (Cooper & Kaplan, 1987, 1998b; Ittner et al., 1997). This logically implies if fewer cost structures exist in an environment, ABC does not necessarily account for the trade-off between implementation effort and accuracy. Thus, this thesis progresses a horserace between both costing systems under an ABC hierarchy and a traditional variable and fixed cost structure.

The last section examines the development of growing information technologies and better trackability of resource consumption. New information technologies are mitigating the impact of transaction costs (Williamson, 1979, 1981) and this should support the collection resource consumption and drivers within the firm. For instance, enterprise resource planning systems now provide more abundant information about production environments than before. This increased transparency also automatizes previous transactional activities such as human data maintenance. The transparency hence sheds new light on the differentiation of indirect and direct costs because they are not predetermined.

Concerning actual guidance (Cooper, 1989; Horngren et al., 2014), simple TVC systems should perform better when there is a large proportion of direct costs. Thus, the last experiments investigate the effects of increasing direct costs on accuracy.

6.2 Model design concept

6.2.1 Conceptual model

Studies of cost system design performance have typically used analytical and numerical analysis (Christensen & Demski, 2003; Labro, 2019). This section is no exception. It uses numerical experiments to manipulate the product technology and cost system designs (see Section 4.5.5). Before presenting the results, the model design concept reviews the model applied. Later, this thesis introduces and explain the conceptual and computational models, followed by a detailed simulation model protocol about the operationalizations that aim to strengthen the credibility of all the outcomes and foster critical discussions.

The progress of the model in Figure 41 illustrates the events along the conceptual model. (1) Initially, realized demand ***q*** pulls the production technology. This leads to the necessary outputs of the processes (***AV***) that consume a certain set of resources (***RC***) for producing the demanded products. Because every consumption level has its price, the production technology causes costs. Next (2), aggregating each resource cost along the resource measures results in total resource costs (***RCC***). Summing along a product computes the benchmark product costs (***PCB***).

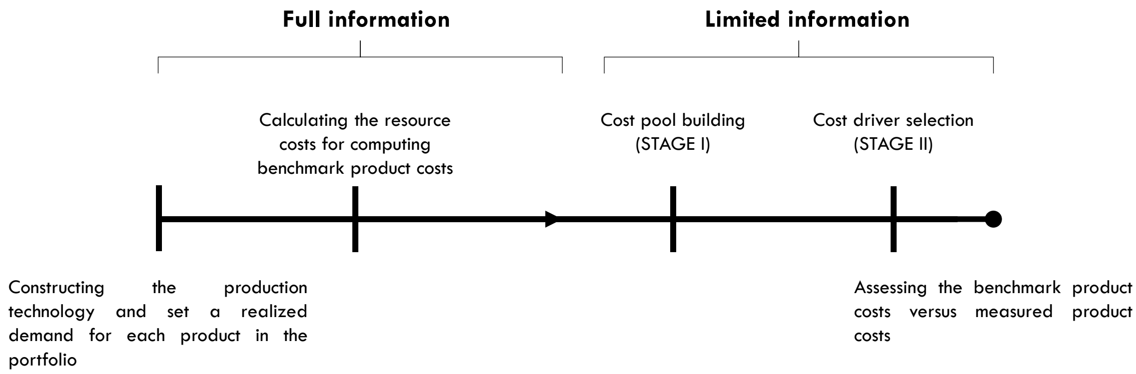

Figure 41: Conceptual walkthrough of one simulation run

Real-world costing systems lack full information and therefore produce approximations of product costs (3). Investigations of cost system design choices start by building cost pools in accordance with specific rules (*CPH*). Then, every cost pool is categorized to a selected cost driver to allocate the costs to the products (*CDH*). While it is nearly infeasible to guarantee a full and perfect information setting, both stages lead to errors in the final approximated product costs ***PCH***.

The last step uses both product costs (***PCB***, ***PCH***) and statistically compares them. The information aggregation and neglection affect the product cost measurement. This impact rises with the error distance between the benchmark and estimated product costs to reflect the accuracy of the heuristics implemented. Hence, cost system design choices can be compared because each is suitable for measuring the costs in a production environment. Next, the computerized model formalizes all the stages of the conceptual model using mathematical models.

6.2.2 Computational model

Based on the conceptual model, the computational model starts by computing a benchmark production environment following Anand et al. (2019). Using the costing framework of Anand et al. (2019) supports the extensive mathematical modeling of the production technology concerning the design elements ***RC***, ***DP***, and ***AV***.[37] The emphasis on product costing in system design choices does not necessarily demand complex engineering design theory. The EAD contains engineering design and economic firm theory, which is advantageous when considering product-centric issues in product-based planning such as NPD. However, fewer product-centric questions may unnecessarily increase complexity. Thus, instead of this engineering product modeling, the identity multiplication of A_{CN_FR} and A_{FR_DP} adapts the EAD to economic firm modeling. This simplification of analytical and numerical research is required (Christensen & Hemmer, 2006) and is applied to A_{AV_RC} as well. Specifically, the latter design matrix has frequently been used, leading to similar outcomes (untabulated results) (Anand et al., 2017, 2019; Balakrishnan et al., 2011). In other words, one can see this identity multiplication somewhat like an accordion that neglects unnecessary elements in the context of the problem system. Finally, using the mentioned identity designs supports the focus on the cost design choices of the relevant systems.

Next, the model draws random numbers from a lognormal distribution to determine realized demand ***q*** for each product ***P***. The products ***P*** and resources ***RC*** create the design matrix A_{P_RC} [*RCs x Ps*] that is embedded in the identity matrix of A_{AV_RC}. This matrix still describes the minimum input resources for one output but uses products and resources. This is relevant because it is the central matrix of consumption considered in the forthcoming experiments.

The resource consumption matrix A_{P_RC} is frequently mentioned as a resource consumption matrix ***RES_CONS_PAT***, which is fundamental in an economic production environment. Research identifies the crucial factors for building the resource consumption matrices that costing systems try to measure (Anand et al., 2019; Balakrishnan et al., 2011; Labro & Vanhoucke, 2007, 2008). For instance, *DENS* shows that sharing resources in ***RES_CONS_PAT*** where *COR* induces a correlation pattern between

[37] The model follows the baseline assumptions of "modern costing" (Christensen & Demski, 1995), namely fixed proportions in production functions combined with Leontief, constant returns to scale (no economies of scale; linearity), cost separability, and, of course, no substitutability among resources.

the resources.[38] Because one should not underestimate the effect of resource consumption modeling, this thesis follows the traditional cost structure of variable and fixed costs. Actual guidance implies that all resources should be multiplied by realized demand (Anand et al., 2019), which covers the full variable cost setting. Other studies have not explicitly carried out this multiplication, as several types of resource consumption are independent of demand (Balakrishnan et al., 2011). This thesis sees a mixture as a valid way for modeling, where the factor *UNIT_SHARE* separates proportional unit-level costs, advocating variable costs, from non-unit-level costs, namely fixed costs. Thus, the model multiplies the unit-level requirements by realized demand to determine the total number of resource units *TCU* (e.g., a material, time, and setup).[39]

Next, the model computes the resource costs ***RCC*** by distributing a constant amount of total costs *TC*=1,000,000 using the parameter *RC_VAR*, which regulates the dispersion of costs at each ***RCC*** (Balakrishnan et al., 2011). A division of each ***RCC*** through the corresponding ***TCU*** computes the resource cost driver ***RCU*** (***RCC***/***TCU***=***RCU***). This driver is then multiplied by demand ***q*** and the minimum requirements from ***RES_CONS_PAT***. Finally, the sums of the individual resource costs end in the benchmark product cost ***PCB***, as indicated by equation (15).

$$\boldsymbol{RCU} \circ \boldsymbol{q} \circ \boldsymbol{RES\_CONS\_PAT} = \boldsymbol{PCB} \tag{15}$$

Despite increasing information technology, gathering full information from a production environment is still infeasible or simply too costly, and thus costing systems make the necessary systematic simplifications through heuristics. Costing systems tend to be two-staged, with cost system designers deciding on the types and amounts of cost pools when selecting a cost driver. The literature highlights organizational, functional, and ABC pool building with simple or indexed cost drivers (Babad & Balachandran, 1993; Balakrishnan et al., 2011; Homburg, 2001; Horngren et al., 2014; Hwang et al., 1993; Labro & Vanhoucke, 2007, 2008; Lanen et al., 2013).

"Cost pool building heuristic CPH"

The heuristic used in this study groups resource costs ***RCC*** into a certain number of cost pools ***CP***. While less explicit, the first "hidden" grouping starts by classifying single resource costs ***RCC*** into resource cost pools ***RCP***. For example, grouping the costs of material, labor, and salary, indirect production activities, and marketing, sales, and development activities result in the homogeneous ***RCP*** of direct and indirect costs. The chosen cost pool-building heuristic next uses all remaining indirect ***RCP*** and builds cost pools by applying systematic simplifications. When all cost pools are consistent, meaning that homogeneity exists within every ***RCP***, there are no errors when aggregating them (Datar & Gupta, 1994; Feltham, 1977).

"Cost driver selection CDH"

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[38] In context of cost measurement, *DENS* = *AV_DENS* = *RC_DENS*.
[39] Section 6.4.3 discusses cost structure theories, where there are further operationalizations and discussions about process and resource modeling.

Assuming that cost system designers set the number of cost pools, the next question concerns how to allocate the costs from the cost pools to product costs, raising the challenge of selecting an appropriate cost driver for every pool. There are several ways of identifying cost drivers, and this thesis applies the "big pool" heuristic. The big pool employs the resource unit driver in terms of the largest cost in cost pools as an allocation base (Anand et al., 2017, 2019; Balakrishnan et al., 2011; Hwang et al., 1993). Imagine that the most expensive resource cost in a cost pool is from a machine. Subsequently, the corresponding activity measures are the machine's output or time usage, which is widely acknowledged for allocating costs. Summarized, cost pool and cost driver selection heuristics systematically neglect information in the full information setting. Taken together, the limited information setting in a cost system is describable by the number of cost pools ***CP*** [1 x *CPs*] and their relative activity driver consumption ***ACT_CONS_PAT*** [*CPs* x *Ps*] in equation (16).

$$\boldsymbol{CP} \circ \boldsymbol{ACT\_CONS\_PAT} = \boldsymbol{PCH} \quad (16)$$

Similar to all the experiments, observing the response from the manipulation and benchmark supports an assessment of the implemented causal mechanisms (Balakrishnan & Penno, 2014). This thesis follows previous research by applying existing error metrics (Labro & Vanhoucke, 2007). Specifically, costing system performance may depend on the Euclidean distance (*EUCD*), mean percentage error (*MPE*), and *%ACC* (≥5% or ≤-5%) (Kaplan & Anderson, 2007). Considering product cost accuracy individually requires more specific measures. Therefore, this thesis also considers the absolute percentage error (*APE*) and percentage error (*PE*) as product cost error measures (Christensen & Demski, 1997). This offers the more decision-relevant error metric shown in equation (17).

$$APE = \left|\frac{PCB - PCH}{PCB}\right|; \; PE = \frac{PCB - PCH}{PCB} \quad (17)$$

6.2.3 Detailed simulation model protocol

Table 9 shows the applied factors responsible for manipulating the production technology. *DENS* reduces the density of the resource consumption matrix *RES_CONS_PAT*. A dense (sparse) matrix is full of non-zero (zero) elements. For example, high *DENS* (0.85) means fewer zero entries in the consumption matrix and suggests more process sharing; conversely, low *DENS*=0.35 is the opposite and this reflects less sharing such as in a specified job shop production. Intuitively, this has significant effects on diversity in resource consumption.

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Table 9: Classification of the parameters

Independent parameters	Control parameters	Dependent parameters
Density of process/resource sharing *DENS* [0.35,0.6,0.85]	Number of products [50]	Euclidean distance (*EUCD*)
Dispersion of realized demand *Q_VAR* [0.5,1, 1.5]	Number of resources [50]	Mean percentage error (*MPE*)
Direct cost share *DC_SHARE* [0,0.2,0.4,0.6]	Number of processes [50]	Absolute percentage error (*APE*)
Cost pools, number of cost pools *CP* [1,2,4,6,8,10,12,14,16,18,20]	Cost pool building *CPH*	Percentage error (*PE*)
Correlation between unit and batch resources *COR* [-0.6,0,0.6]	Cost driver selection *CDH*	
Resource cost dispersion *RC_VAR* [0.35,0.5,0.75]	Simulation repetitions [20][1]	
Unit-level share in terms of costs *UNIT_SHARE* [0.3,0.5,0,7]		
Measurement errors *ERROR* [0.1,0.3,0.5]		

[1] There were no severe numerical deviations in the mean and variance for 20, 50, 100, and 1000 repetitions.
Identity design matrices: A_{CN_FR}; A_{FR_DP}; A_{AV_RC}

Importantly, the dispersion of realized demand ***q*** along the product portfolio is modeled using *Q_VAR*. Although mass customization is desired, firms still have more and less produced products. In detail, firms frequently have a few "standard" products that tend to be produced in large quantities combined with less produced product variants that often have more unique functional requirements. When *Q_VAR* is high (1.5), it leads to a few standardized variants with huge demand and many less requested product variants. For example, this reflects a portfolio where 10 products own 70% of total demand. By contrast, the top 10 products have a smaller share of 35.9% when *Q_VAR* is low (*Q_VAR*=0.5).[40]

The new parameter in the model is the direct cost share of total costs *DC_SHARE*. For instance, higher shares of direct costs (*DC_SHARE*=0.7) are common in manufacturing, whereas service sectors (*DC_SHARE*=0.4) might possess more substantial overhead shares (Al-Omiri & Drury, 2007; Drury & Tayles, 2005). Thus, this thesis models direct costs directly from resource consumption by splitting it into direct and overhead costs (see Section 6.5 for the detailed modeling).

CP sets the number of cost pools and cost drivers. As important as this factor are the used cost system design heuristics, cost pool building heuristics (e.g., cost centers), and cost driver selection heuristics (e.g., product units). These heuristics represent a particular mechanism for grouping resources to cost pools or using underlying measures to allocate costs to objects to indicate the efforts of information gathering (Balakrishnan et al., 2011).

RC_VAR defines the skewness of resource unit prices ***RCU*** by defining different distributions over all resource costs ***RCC***, either equal or dispersed (see Balakrishnan et al. (2011). For example, for a low value of *RC_VAR* (i.e., 0.4), resource costs have uniform distributed costs and magnitudes. For higher

[40] To substantiate the chosen variable levels, empirical and conceptual sources were considered. The conceptual data were collected from standard textbooks (Franz & Kajüter, 2002; Horngren et al., 2014) and the empirical data were gathered from business reports (i.e., VW and Toyota) and qualitative interviews (anonymous).

values of *RC_VAR* (i.e., 0.7), few resources dominate, resulting in a stratified and skewed distribution of resource costs.

COR reflects the correlation between consumption patterns, which refers to the ABC hierarchy. In empirical and analytical studies, cost categories do not necessarily correlate positively with each other. In particular, unit-level costs and variable costs are strictly proportional to the production output. Conversely, non-unit-level costs and fixed costs do not behave proportionally (Ittner et al., 1997). *COR* implements this circumstance by embedding different correlations between the resource (i.e., *COR*=0.6).

UNIT_SHARE determines the number of unit-level activities, which behave proportionally to increases in production units such as variable costs. Previous studies have argued that non-unit-level activities are an indicator of complex cost systems such as ABC (Abernethy et al., 2001; Cooper & Kaplan, 1987). Consequently, the model recognizes a range of *UNIT_SHARE* of 70%, 50%, and 30%, which implies higher and lower non-unit-level costs. When *UNIT_SHARE* is high (*UNIT_SHARE*=0.7), a few batch- or product-level activities concern the ABC hierarchy, while there is a large amount of unit-level activity. For instance, when the environment contains 50 activities, *UNIT_SHARE* of 0.7 defines 35 activities as unit-level costs and 15 as non-unit-level costs.

Finally, the (random) measurement error *ERROR* will distort the allocation bases randomly. The model thus adopts the modeling strategy of Balakrishnan et al. (2011), which acknowledges the experimental finding of Cardinaels and Labro (2008), who find a measurement error of around ~37%. Following this observation, the three error levels of 10%, 30%, and 50% are reasonable.

Total costs are fixed at TC=1,000,000; the number of products, processes, and resources are fixed as well (RCs=50; AVs=50; Ps=50). The batch-level costs allocated at all batch-level activities are randomly drawn around 30% and 50% following the empirical observations.[41] The descriptive statistics in Table 10 provides the descriptive statistics following Balakrishnan et al. (2011) show the changes by manipulating the independent parameters and provide additional information on how the simulation model behaves.

[41] The empirical literature finds a percentage value of 35% for batch- and product-level costs (e.g. Ittner et al., 1997), which is adapted by Balakrishnan et al. (2011).

Table 10: Descriptive statistics: Simple and complex costing

Descriptive statistic	Unit	Average values			
Variation in resource costs (using parameter ***RC_VAR***) [2]		Global Average	Low dispersion (*RC_VAR*=0.4)	Medium dispersion (*RC_VAR*=0.55)	High dispersion (*RC_VAR*=0.7)
Percentage of costs in the top 10 costliest resources	[%]	**45.11**	40.16	41.45	49.42
Density of consumption matrix (using parameter ***DENS***) [3]		Global Average	Little sharing of resources (*DENS*=0.35)	Medium sharing of resources (*DENS*=0.6)	High sharing of resources (*DENS*=0.85)
Percentage of zero entries in the consumption matrix	[%]	**45.01**	69.98	44.98	20.01
The average number of objects consuming a resource (max.=50)	#	**12.93**	15.01	27.52	39.94
Average range in the consumption of a resource across products	[%]	**27.49**	17.62	11.92	9.24
Correlation between realized demand and average unit-level resources	#	**0.54**	0.33	0.54	0.76
Variant in realized demand (using parameter ***Q_VAR***)		Global Average	Equal demand (*DENS*=0.5)	Moderate diverse demand (*DENS*=0.5)	Much diverse demand (*DENS*=1.5)
Percentage of realized demand in the top 10 demand products		**53.29**	35.90	54.00	69.98
Importance of resource devoted to non-unit activities (using parameter ***COR***)		Global Average	Similar consumption pattern (*COR*=0.6)	Intermediate consumption pattern (*COR*=0)	Dissimilar consumption pattern (*COR*=-0.6)
Correlation between realized demand and unit-level resources	#	**0.54**	0.54	0.54	0.4
Average correlation between unit and batch resources[1]	#	**-0.01**	0.02	0.00	-0.05
Variation in realized demand (using parameter ***VOL_VAR***)		Global Average	Similar demand across products (*VOL_VAR*=0.5)	Intermediate demand across products (*VOL_VAR*=1)	Skewed demand across products (*VOL_VAR*=1.5)
Percentage of production units in the top 10 product costs	[%]	**53.35**	35.96	53.99	70.16
Correlation between realized demand and average unit-level resources	#	**0.54**	0.430	0.579	0.622
Sharing unit-level activity costs in the environment (using parameter ***UNIT_SHARE***)		Global Average	Less advanced manufacturing technology (0.3)	Moderate advanced manufacturing technology (0.5)	Much advanced manufacturing technology (0.7)
Percentage of costs in the top 10 resources	[%]	**45.12**	54.36	41.68	39.34
Average range in the consumption of a resource across products	#	**12.96**	10.14	12.93	15.82

[1] The correlation values are imprecise because *DENS* is distorted due to inducing zeros. For example, having *DENS*=1 the technology is responsible for clear correlation settings. [2] The resulting distribution of the total resource cost pool vector *TRC* is in the middle of Balakrishnan, Hansen, and Labro (2011) with 35±5% and Anand, Balakrishnan, and Labro (2017) with 55±9%. This decision outweighs the advantages and disadvantages of size-based heuristics and suggests robustness in general. [3] Resource sharing (*DENS*) seeks to find the middle between the previous modeling of Balakrishnan et al. (2011) and Anand et al. (2017). Therefore, the global averages of this thesis lay between these former studies by ±5%.

6.3 Evaluating simple costing systems

6.3.1 Simple costing systems

This subsection compares simple TVC heuristics and their resulting error sensitivities with suspected antecedents. Despite lacking the clarity of the limitations and adequacy of simple costing systems, there is a strong presumption that they are also inaccurate and thus identical (Drury, 2015; Horngren et al., 2014; Lanen et al., 2013). However, the general shift toward complex costing has not diffused, and simple systems are still being used in the industry. Hence, this thesis performs experiments to assess distinct single cost drivers and ascertain whether they are more or less identical. This question may offer generalizable results and thus new guidance on applying simple TVC heuristics.

The most straightforward cost designs contain just one cost pool and cost driver encompassing and allocating all overheads (Brierley, 2008; Drury & Tayles, 2005). Single cost drivers are mostly volume-based, referring to their availability and simplicity as well as the neoclassical assumption that all production functions depend on the units (Christensen & Demski, 1995). This thesis uses a sample of five single overhead drivers drawn from the literature (Cooper & Kaplan, 1987, 1988; Drury, 2015; Hansen & Mowen, 2006; Horngren et al., 2014; Lanen et al., 2013; Mowen, Hansen, & Heitger, 2011; Shank & Govindarajan, 1988). The selected cost driver selection heuristics of TVC systems are the allocation bases of total production units (DIV), average direct labor hours (DLH), predetermined overhead allocation with a unit-level process (UAM) and non-unit-level process (NUAM), as well as direct material requirements (DM).

DIV, which may be the most prominent and most frequently available single cost driver (Shank & Govindarajan, 1988), uses the relative weights of the number of products in comparison to total production output Σq. Using direct labor hours for overhead allocation (DLH) is another standard approach (Horngren et al., 2014). This driver incorporates the direct labor hours of each product in a period and builds weights relative to total labor hours. Notably, the driver does not strongly rely on labor because machine hours are also applied. Whether labor or machines, both cost drivers positively correlate with manufacturing overheads (Foster & Gupta, 1990, p.322-325).

Another driver uses the material costs of each product to build the relative weights for the subsequent cost allocation (DM) as an allocation base. Material costs often account for a large share of a firm's costs, making them suitable as a driver for overheads as well. Cause-and-effect allocation bases are based on actual process use instead of aggregated or average measures. UAM and NUAM select the costliest unit-level or non-unit-level process as an allocation base (i.e., expensive machine hours). Summarized, all the techniques are advantageous from an information perspective, but they have not thus far received detailed investigation.[42]

[42] See Appendix 10.1 for the detailed formalization of the cost driver selection heuristics.

6.3.2 Assessing simple cost driver heuristics

The first experimental design in Table 11 reflects the parameters considered. Production technology has been used to investigate cost system performance by previous studies (Anand et al., 2017, 2019). Using 50 products and 50 processes leads to 50 resources, where the repetition is at 20 runs. This amount is sufficient for a covariance steady-state (Law, 2014a). In simple words, the experimental design is able to investigate the advantages and disadvantages of simple volume-based cost driver heuristics in a more general setting.

Table 11: Experimental design – Assessing simple cost driver heuristics

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35, 0.6, 0.85]	Products	50	Euclidean distance [EUCD€]
Q_VAR	[0.5,1,1.5]	Processes	50	
RC_VAR	[0.4,0.55,0.7]	Resources	50	
UNIT_SHARE	[-0.6,0,0.6]	Repetitions	20	
COR	[0.3,0.5,0.7]	Total costs	1,000,000€	
ERROR	0	CP	1	
		CPH	Random	
		CDH	*See 10.1*	
n= 4,860 (3^5*20)				

The results in Figure 42 demonstrate the accuracy differences between the selected cost driver heuristics chosen by an estimated mean plot. Interestingly, all the aggregated volume-based cost driver heuristics (DIV, DLH, DM) are seemingly less distorted in contrast to the cause-and-effect drivers (UAM, NUAM). This outcome was unexpected because guidance is a *cause-and-effect criterion* (Horngren et al., 2014), namely a rule of thumb that aims to use activity measures instead of aggregate or average labor hours and production units. Hence, the cost driver heuristics (DIV, DLH, DM) have a comparative advantage over the cause-and-effect cost drivers.

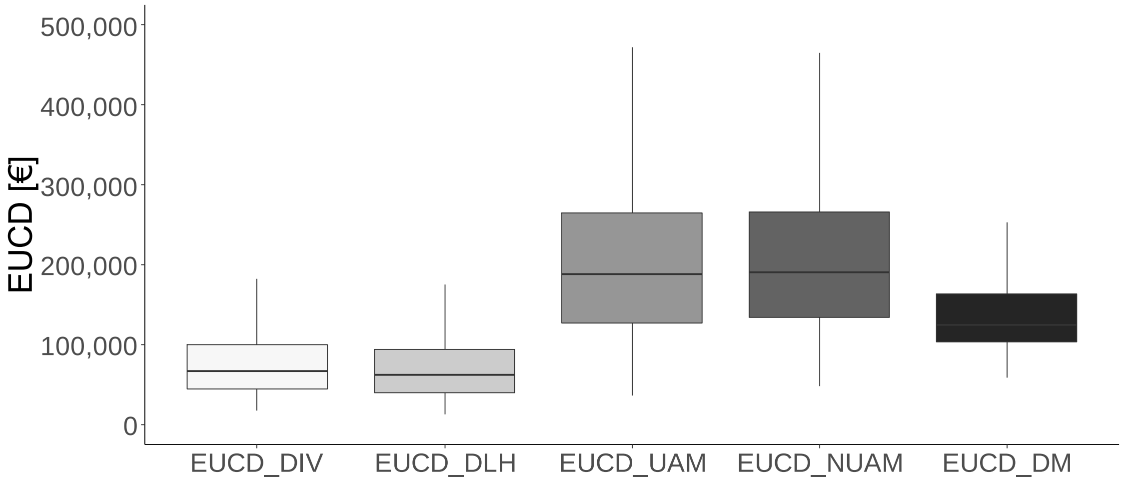


Figure 42: Assessing simple cost driver heuristics in a one-pool costing system

Additionally, Figure 42 indicates significant error variance for UAM and NUAM, probably conditional of their closeness to the production environment. The aggregated volume-based cost drivers are robust to varying environmental factors while having seemingly less dispersed errors in contrast to the cause-and-effect cost drivers, as shown by the width of the boxplots. Less sensitivity among simple cost drivers is regularly stated as a disadvantage (Horngren et al., 2014), nonetheless, it supports robustness to errors either. The cause-and-effect cost drivers are more sensitive to the production environment, which includes stochasticity such as measurement errors . This thesis therefore concludes that the aggregated cost drivers tend to be robust to environmental factors compared with the single cause-and-effect drivers. Hence, simple allocation bases do not behave similarly, especially product units and direct labor hours are seemingly efficient.

Regressing the environmental parameters on the EUCD in Table 12 shows the heuristics' sensitivities to errors and demonstrates that they behave dissimilarly in statistical metamodels, too. In detail, consider the density of resource sharing, designed as *DENS*. This parameter has less effect on DIV (B=-0.33, η^2=0.179), DLH (B=-0.14, η^2=0.102), and DM (B=-0.23, η^2=0.02) in contrast to the cause-and-effect drivers of UAM (B=-0.53, η^2=0.69) and NUAM (B=-0.41, η^2=0.65). Hence, the aggregated drivers are less error-sensitive to diversity in the production environment.

Table 12: Regression table of simple cost driver heuristics

	DIV			DLH			UAM			NUAM			DM		
	B	η²	F	B	η²	F	B	η²	F	B	η²	F	B	η²	F
DENS	-0.33	*0.18*	32	-0.14	*0.10*	417	-0.53	*0.69*	9,750	-0.41	*0.65*	8343	-0.23	*0.02*	65
Q_DIV	0.73	*0.56*	152	0.83	*0.53*	5,239	0.71	*0.41*	3,280	0.38	*0.37*	2871	0.67	*0.42*	3,398
UNIT_SHARE	-0.19	*0.01*	11	-0.05			0.09			0.20	*0.03*	91	-0.02		
RC_VAR	0.05			0.06			-0.01			0.02			0.01		
COR	-0.06			-0.10			-0.07			-0.03			-0.05		
DENS x Q_DIV	-0.05			-0.11			-0.20	*0.03*	119	-0.11	*0.01*	34	-0.01		
DENS x UNIT_SHARE	0.42			0.14			-0.28			-0.90	*0.02*	84	0.31		
n		4,860			4,860			4,860			4,860			4,860	
R^2-adj		0.60			0.55			0.74			0.71			0.43	

Multicollinearity VIF Controlled≤5
The model and all shown effects are significant $p<0.05$
B = Standardized Regression Coefficients, η^2 = Effect sizes F = F-value from an ANOVA model type III;
Interaction effects of $\eta^2<0.01$ are excluded.

Q_VAR seems to be the strongest error driver among all the heuristics (B(DIV)=0.73, B(DLH)=0.83, B(UAM)=0.71, B(NUAM)=0.38, B(DM)=0.67). The literature advocates that the increasing volume diversity from a skewed demand distribution is a source of distortion when using volume-based allocations (Cooper & Kaplan, 1987). The regression models identify *Q_VAR* as an impelling parameter. One can conclude that stratified demand (i.e., few standard and many specific variants) in a product portfolio causes diversity in unit-level consumption. In sum, *DENS* and *Q_VAR* are materialistic drivers and indicators of errors in product cost approximations.

Table 12 highlights that *UNIT_SHARE* has negative and positive error effects, but overall a smaller effect size (B(DIV)=-0.19, B(DLH)=-0.05, B(UAM)=0.09, B(NUAM)=0.20, B(DM)=-0.02) than *DENS* and *Q_VAR*, which indicates less power and relevance. This was slightly unexpected because a lower *UNIT_SHARE* is associated with more batch- and product-level consumption. Further, the number of different processes and their drivers is not relevant per se because the costs are on average constant (untabulated result), suggesting that the number of distinct processes within a production technology does not infer more errors.

RC_VAR and *COR* have less impact on distortions in their magnitude and effect size. Both have less statistical power on the EUCD and hence are not strictly indicators for facilitating cost system design choices. The regression models in Table 12 recognize the effects of statistically relevant interaction effects. Most models with a large sample are full of interaction effects, but these are less observable in the raw data. Consequently, the identification of interactions demands convincing statistical power; therefore, this thesis neglects interactions with less statistical power to prevent exaggerating the qualitative interpretations of rather statistical artifacts.

The interaction plots in Figure 43 present the interaction effects, illustrating the estimated means under these effects through bar plots, where *DENS* x *Q_VAR* is the most remarkable in NUAM and UAM. *DENS* x *Q_VAR* has the most statistical relevance in terms of the regression coefficient, effect size, and F-value (i.e., UAM B=-0.20, $n^2=0.03$, F-value=119). This implies that less process and resource sharing between products (low *DENS*) hampers an additional distortion of *Q_VAR*. Hence, less sharing of resources among products mitigates the impelling strength of different production volumes in simple cost drivers.

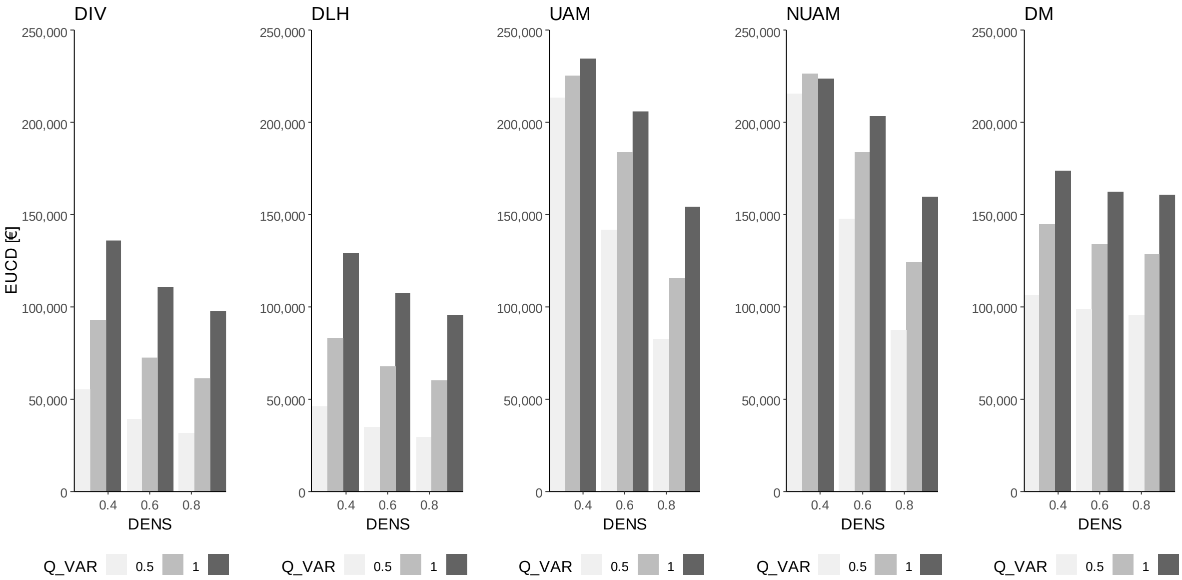


Figure 43: Interaction plots between *DENS* and *Q_VAR*

To sum up, simple (i.e., classical and traditional) allocation bases embedded in simple TVC systems have different levels of accuracy. The data suggest that cause-and-effect drivers (UAM, NUAM) are unsatisfactory as single cost drivers. DIV, DLH, and DM, conversely, are more accurate even though they are indifferent to production technology. This provides an interesting picture of robustness when applying aggregated drivers. By contrast, UAM and NUAM are less convincing and may need more cost pools and drivers.

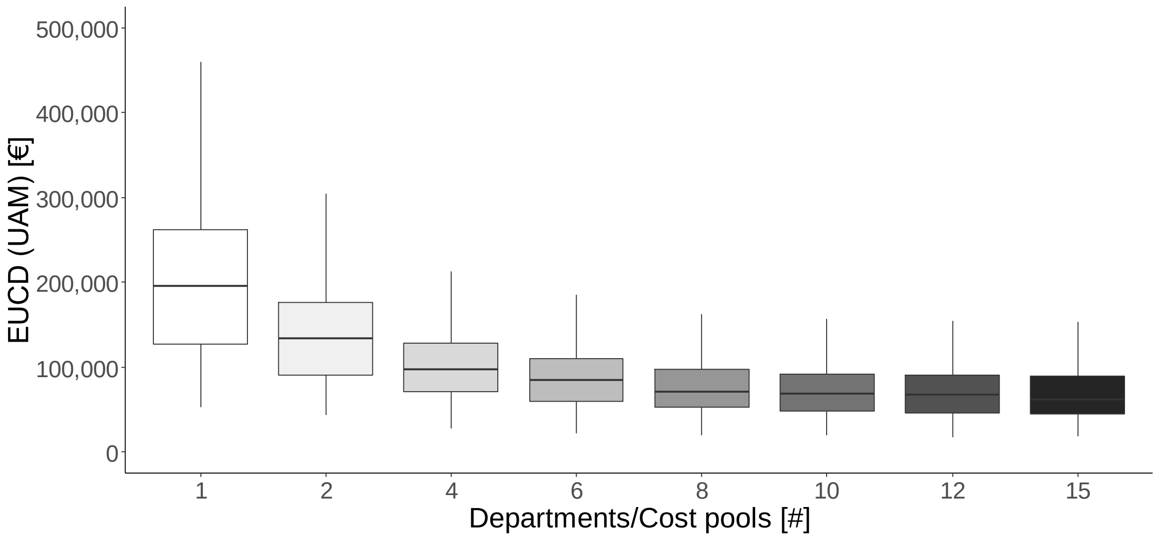


Figure 44: Assessing the costing error among increasing departments and unit-level allocation bases

In a departmental setting, as shown in Figure 44, the data show the expected improvement compared with a single allocation basis application of UAM. Departments are cost pools but tend to group resources by functional (similar to activity cost pools) or organizational rules (probably more “random”). This structure is often suspected in German cost accounting (Boons, Roberts, & Roozen, 1992). The shown experiment follows an organizational structure (“random”) with a maximum of 15 departments.[43,44]

Figure 44 demonstrates accuracy gains by increasing departments that converge to DLH and DIV at around 10 and overtake them around 15. The shown cost system design with UAM records an EUCD of 75,011€ with 10 departments. Interestingly, this accuracy is comparable to previous aggregated allocation bases such as DLH (76,750€) and DIV (82,178€). Continuing to 15 cost pools, UAM increases to 70,050€ and finally outperforms DLH and DIV. Hence, despite the exclusive usage of volume-based allocation bases, cost system accuracy can rise with extensive efforts.

6.3.3 Cross-subsidization in traditional volume-based cost systems

Cooper and Kaplan (1998a) recommend applying *“... ABC systems where there is a large variety of products. For example, standard and custom products, high-volume, and low-volume products”*. This guidance results from the fact that TVC systems cross-subsidize high volume (simple) and low volume (complex) products (Horngren et al., 2014). Indeed, simple costing systems do not resolve complex resource consumption patterns because they solely use one type of allocation base. Standard textbooks introduce this case to highlight the comparative advantage of ABC systems (e.g., Drury, 2009, p. 190; Hansen & Mowen, 2006, p. 124f.; Horngren et al., 2014, p. 158f.; Lanen et al., 2013). In these textbooks, simple (high volume) products are overcosted and complex (low volume) products are undercosted. However, while they are excellent teaching examples for cost distortions in cost accounting courses, they are likely to fail to mirror more realistic circumstances (see the Appendix for an example).

Cross-subsidization overcosts products with high unit-level costs and undercosts products with low unit-level costs on the condition that not all overheads behave proportionally to the production units. If firms’ overhead allocation uses unit-level processes, high volume products have higher overhead costs because the implementation of non-unit-level overheads is ignored. For complex products, this is the opposite, while complexity leads to undercosting. Despite this systematic deviation, large-scale analysis of this phenomenon is lacking besides the above-mentioned simple practice and teaching cases.

This thesis seeks to add generalizable evidence to this mechanism when analyzing product costs in a TVC system with *DIV*. The experimental design is similar to that in Section 6.3.2; however, it now turns to the product level (*PE* and *APE*) instead of the system level (costing system performance). The

[43] The experiments underline the limitation that the maximum available unit-level activity is 15 because a *UNIT_SHARE* of 0.3 reduces the processes ($50 \times 0.3 = 15$).
[44] Untabulated results of NUAM show congruent qualitative behavior when increasing cost pools and allocation bases.

experimental design in Table 13 is similar to the previous one but has more repetitions, thus yielding a sample of 1,215,000 product cost measures.

Table 13: Experimental design: Cross-subsidization experiment

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35, 0.6, 0.85]	Products	50	Percentage error [PE%]
Q_VAR	[0.5,1,1.5]	Processes	50	Absolute percentage error [APE%]
RC_VAR	[0.4,0.55,0.7]	Resources	50	
COR	[-0.6,0,0.6]	Repetitions	100	
UNIT_SHARE	[0.3,0.5,0.7]	Total costs	1,000,000€	
ERROR	0	CP	1	
		CPH	Random	
		CDH	*DIV*	
n= 1,215,000 ; 24,300 (3^5* 100) x 50 products				

Figure 45 shows that product costs – factorized by their unit-level costs through *COST_SHARE* – suffer from cross-subsidization. The presumed pattern is that low volume products, potentially identifiable by a lower unit-level cost share (*COST_SHARE* = 0 to 50%), are mainly biased downward. When products have a higher unit-level cost share, they may be overcosted, as appears for the first time in a boxplot. This result is in line with the theory, but surprisingly under- and overcosting are not predictable when only considering *COST_SHARE*.

Figure 45 details the unexpected result that despite large unit-level consumption, overcosting is by no means clear. The general phenomenon of cross-subsidization has indeed been confirmed following theory and practical guidance; however, there is large variance in every boxplot, which indicates less precision for determining over- and undercosting. Specifically, high unit-level product costs can lead to over- and undercosting with a slight tendency toward the former. Despite needing further consideration, this thesis supposes that the under- and overcosting behavior of TVC systems is not straightforward.

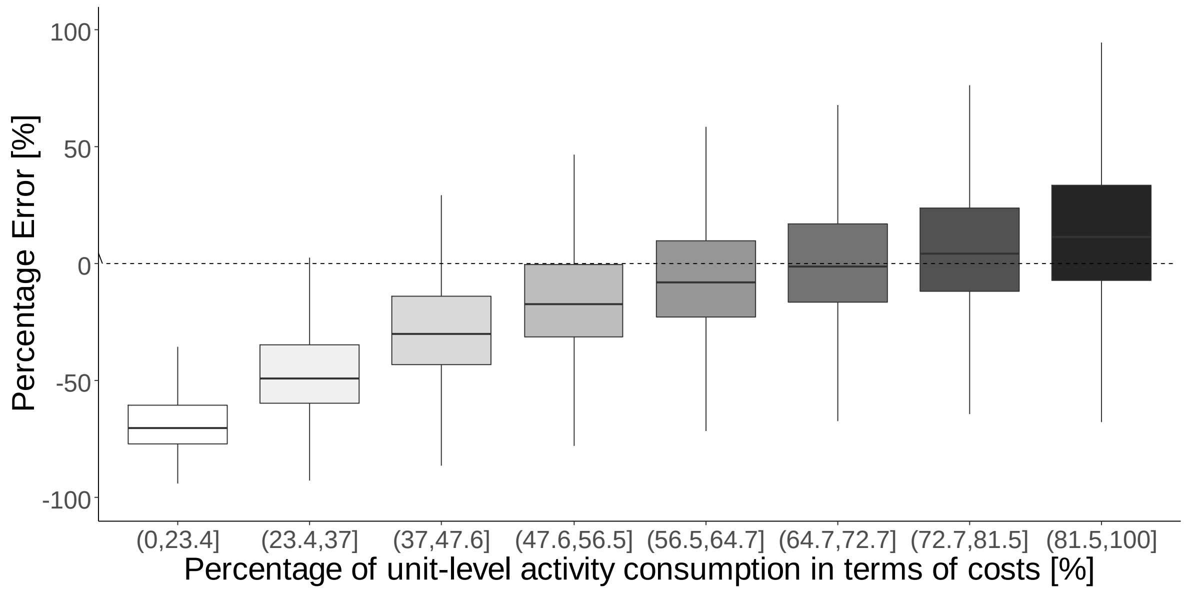


Figure 45: Cross-subsidization when applying the volume-based cost driver heuristics

Extending the analysis of Figure 45, Table 14 shows an ordinary least squares regression to identify the error driver and claims that not only *COST_SHARE* is decisive. Figure 45 shows that less volume-based products are predominantly undercosted even when they incur over 65% unit-level costs. Considering *COST_SHARE* through the metamodel, *PE* (B=0.55, n²=0.31, F-value=469,190) and *APE* (-0.35, n²=0.11, F-value=161,066) confirm the impact on over- and undercosting behavior. Surprisingly, higher unit-level costs tend to reduce *APE*, which has not previously been identified. Therefore, one could anticipate that undercosting is prominent – as stated earlier – and identifiable through the share of non-unit-level costs; nonetheless, predicting overcosting is not as straightforward as may be expected.

Table 14: Regression table of the error drivers in TVC systems

	PE [%] [+/-]			***APE*** [%] [+]		
	B	η^2	F	B	η^2	F
INTRA	-0.21	*0.02*	19,749	0.12	*0.10*	5,261
INTER	0.10		16,122	0.17	*0.03*	39,879
COST_SHARE [%]	0.55	*0.31*	469,190	-0.35	*0.11*	161,066
INTRA x *INTER*	-0.02	*0.01*	15,498	-0.02	*0.01*	10,188
COST_SHARE x *INTRA*	0.02	*0.05*	64,508	0.01	*0.01*	13,439
COST_SHARE x *INTER*[1]	-[1]	-[1]	-[1]	-[1]	-[1]	-[1]
DENS	-0.03		155	-0.15	*0.03*	42,197
Q_DIV	-0.09	*0.01*	15,792	0.25	*0.08*	107,780
UNIT_SHARE	0.00		20	-0.02		679
RC_VAR	0.01		250	0.02		674
COR	0.00		1	0.00		12
n		1,214,591			1,214,591	
R^2-adj		0.46			0.38	

Multicollinearity VIF Controlled≤5
The model and all shown effects are significant $p<0.05$
B = Standardized Regression Coefficients, η^2 = Effect sizes F = F-value from an ANOVA model type III;
Less intense interaction effects in terms of $\eta^2<0.01$ are excluded.
[1] The interaction term has high collinearity and is excluded, because its coefficients are not consistent.

Next, this thesis applies the introduced heterogeneity measures to quantify the impact of products' complexity. In detail, products with high *INTRA* and *INTER* (*APE*: *INTRA*: B=0.12, η^2=0.10, F-value=5,261, *INTER*: B=0.17, η^2=0.03, F-value=39,879) tend to be prone to costing errors. Common guidance claims that simple products are biased upward, whereas complex products are biased downward (e.g. Cooper, 1989). Recall that *INTRA* and *INTER* reveal products' technology diversity as well as position in the product mix. High *INTRA* means that a product uses various dissimilar processes within a complex production technology. High *INTER* suggests that this product is dissimilar to other products in the mix, probably either seldom or highly demanded product variants. Considering the direction, high *INTRA* (*INTER*) biases product costs downward (upward) (i.e., *PE*: *INTRA*: B=-0.21, η^2=0.02, F-value=19,749). This thesis therefore suggests that complex products tend to be sensitive to costing errors, whereas simple ones are robust to costing errors.

COST_SHARE, *INTER*, and *INTRA* share interaction effects that disentangle cross-subsidization in a product portfolio further. Figure 46 illustrates the interaction effects using an estimated mean plot. As the regression model predicts, *COST_SHARE* x *INTRA* has a large impact (i.e., B=0.02, n^2=0.05, F-value=64,508). Unfortunately, *COST_SHARE* x *INTER* suffers from multicollinearity; nonetheless, the interaction plot in Figure 46 offers a more credible insight than falsely estimated coefficients.[45]

Figure 46 reveals that products with large *COST_SHARE* are typically sensitive to overcosting; yet, higher levels of *INTRA* and *INTER* are necessary. Figure 46 suggests that a rather complex production technology (high *INTRA* or high *INTER*) is an indicator of overcosting, whereas less complexity dampens overcosting. This finding is interesting because it does not show the presumed association between simple products and overcosting strictly.

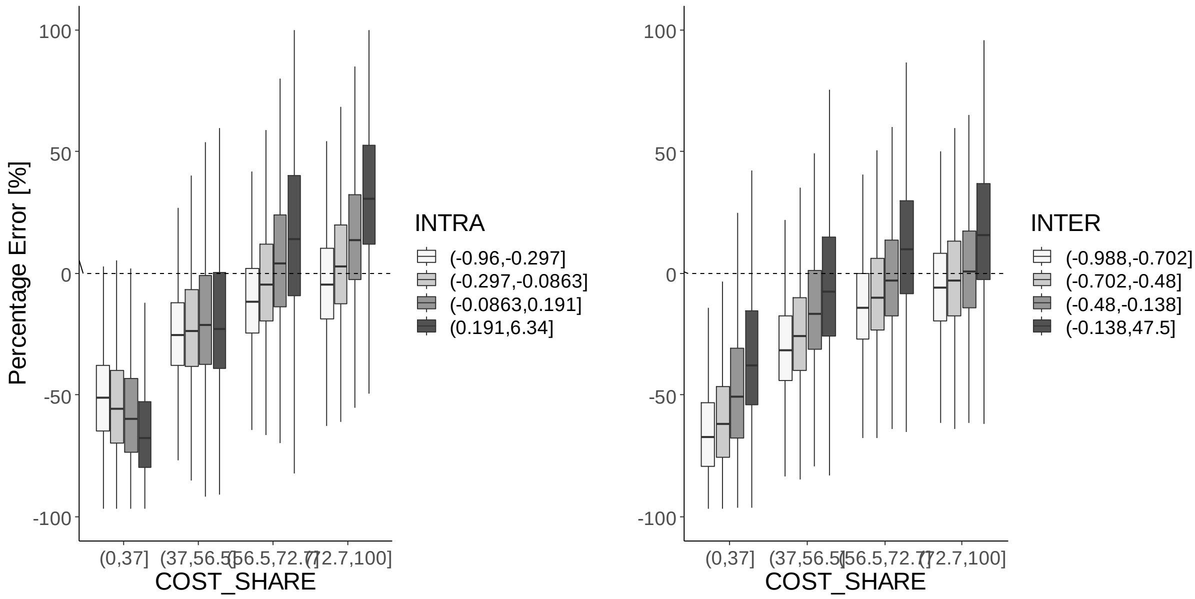


Figure 46: Interaction plots of heterogeneity and product costs' shares of unit- and non-unit-level costs. Left panel: *INTRA* / Right panel: *INTER*

In detail, Figure 46 depicts that high *COST_SHARE* under low *INTRA* and *INTER* results in less biased product costs. Simple mass-produced products have less *INTRA* but more *INTER*, whereas less *INTRA* clearly indicates less overcosting. In combination with the regression coefficient showing that unit-level costs lower costing errors, overcosted products may have higher levels of *INTRA* or *INTER*. Following this argumentation, this thesis concludes that simple high volume products *are not strictly* overcosted as taught in cost accounting as long as they are not too *complex*.

[45] Multicollinearity in interaction effects is common and does not necessarily distort the regression coefficients. However, the multicollinearity in this case was over 100, indicating that both try to explain the same variance. This hints at a more subtle effect such as partial mediation. A subsequent but untabulated analysis confirmed the causal mechanism by identifying that large production units increase unit-level activity consumption as *INTER* increases.

6.4 Assessing simple and complex costing systems

6.4.1 Horserace between simple and complex product costing

Complex costing systems are presumed to offer a competitive advantage by having more accurate product costs (Cooper & Kaplan, 1998b); however, there is still inconclusive evidence (Anderson et al., 2002; Gosselin, 2006; Krumwiede & Charles, 2014). ABC systems have been diffused less than simple TVC systems in recent decades (Al-Omiri & Drury, 2007). Despite this ambiguity, few studies of cost design choices have been conducted.

Comparative assessments between simple TVC and complex ABC systems using fair scenarios and varying contextual factors are thus far unreliable. An exception is Christensen and Demski (2003), who disentangle the advantage of simple and complex costing under non-linearity. Following their study, this thesis explores when and in which situations sophisticated ABC systems provide an advantage over traditional cost accounting systems. To conclude, this comparative assessment seems promising, as the claim concerning ABC's superior accuracy seems not to be well founded despite its prevalence.

Consequently, there is tension in a horserace between product costing. The ABC system consists of the most and least informative heuristics in accordance with Balakrishnan et al. (2011). In detail, the *CPH* and *CDH* combinations apply "correl-size" and "big pool". In further scenarios, this thesis accounts for the random measurement errors (*ERROR*=0.1,0.3,0.5) for both. In this experiment, *UNIT_SHARE* and *RC_VAR* are uniformly randomized, designated as *RND*, due to their negligible effects. This aids computational performance and focuses the model on its relevant factors but does not exclude their effects. Simple TVC systems incorporate one cost pool, aiming at the total sum of overheads, and *DIV* as an allocation base. Table 15 shows the experimental design.

Table 15: Experimental design: Horserace between simple and complex costing systems

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35, 0.6, 0.85]	Products	50	Euclidean distance [EUCD€]
Q_VAR	[0.5,1,1.5]	Processes	50	
RC_VAR	[0.4,RND,0.7]	Resources	50	
UNIT_SHARE	[0.3,RND,0.7]	Repetitions	20	
COR	[-0.6,0,0.6]	Total costs	1,000,000€	
ERROR	[0.1,0.3,0.5]	TC(CPH)	Random	
CP	[1,2,4,…,18,20]	TC(CDH)	DIV	
		ABC(CPH)	Correl-Size	
		ABC(CDH)	Big pool	
n= 17,820 (3^5* 11 * 20)				

Figure 47 shows an estimated mean plot where the ABC system dominates the TVC system for more than 10 cost pools. The advantage of ABC systems is noted when the number of cost pools ~*CP*=6. Nonetheless, in some scenarios, both systems can be somewhat similar (even at *CP*=10). This evidence further substantiates the intangible rule of thumb that 10 cost pools are sufficient (Balakrishnan et al., 2011). As a result, the study claims that ABC systems require a specific number of cost pools to be advantageous over a simple TVC system.

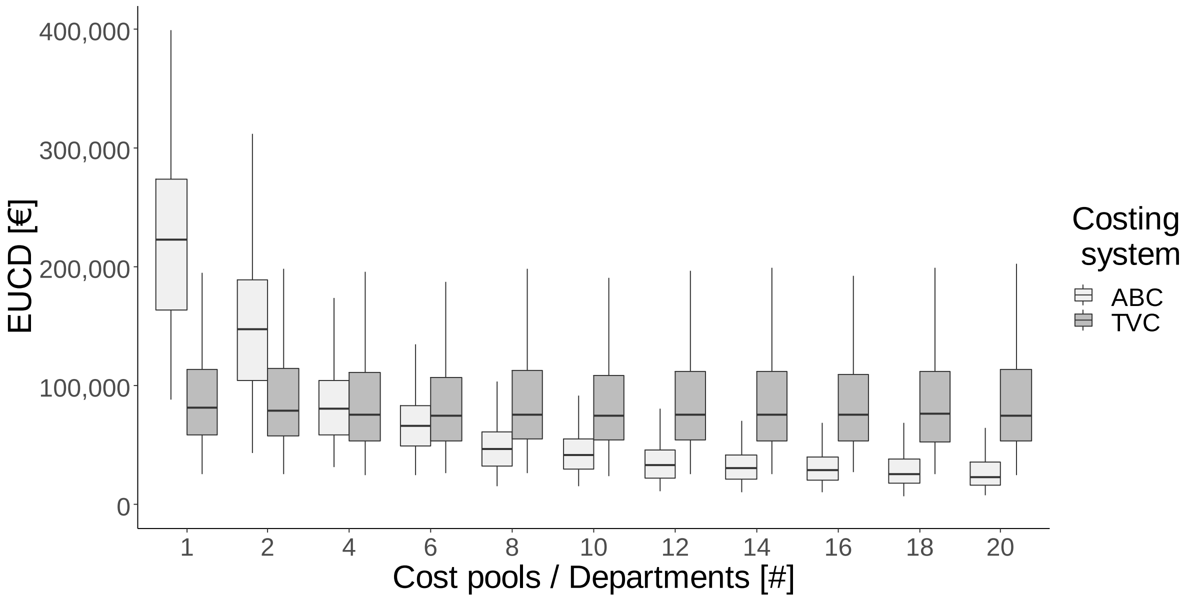


Figure 47: Horserace between simple TVC and complex ABC systems

Disentangling the error drivers further, Table 16 shows statistical evidence that *Q_VAR* is the most relevant error driver. As mentioned, *Q_VAR* reflects the diversity in the distribution of realized demand. This well-known phenomenon in research leads to severe drawbacks for TVC systems (B(ABC)=0.15, η^2(ABC)=0.06 vs. B(TVC)=0.74, η^2(TVC)=0.59). Moreover, *DENS* differs little between the considered systems, as both are prone to diversity (Labro & Vanhoucke, 2008; Shank & Govindarajan, 1988). Interestingly, the measurement error *ERROR* does not have a substantial influence on either. Overall, complex ABC systems win the horserace among existing modeling and parameters when increasing the number of cost pools (~10).

Table 16: Statistical regressions for evaluating simple TVC and complex ABC systems

	ABC SYSTEM [EUCD] / [€]			TVC SYSTEM [EUCD] / [€]		
	B	η^2	F	B	η^2	F
DENS	-0.30	*0.20*	3,258	-0.28	*0.17*	3,232
Q_VAR	0.15	*0.06*	582	0.74	*0.59*	24,727
ERROR	0.05		93	0.02		20
CP	-0.74	*0.60*	25,406	-0.02		16
n		17,057			17,347	
R^2-adj		0.63			0.89	

Multicollinearity controlled in the linear model VIF < 5;
All models are significant (p<0.01);
B = Standardized Regression Coefficients, η^2 = Effect sizes F = F-value from an ANOVA model Type III;
The full sample is 17,820 as shown in Table 12; nonetheless, extreme values are truncated to sustain the normality assumption of regression modeling; outliers above 400,000 €.

The outcome of the horserace is expected because ABC outperforms TVC, as suggested by research (Cooper & Kaplan, 1998b). Although the expected outcome of the experiment is intuitive, it yields an additional insight. First, the recommendation of 10 cost pools for ABC systems meets the threshold for beating TVC (Balakrishnan et al., 2011). This performance indication gradually fills the overall picture between simple and complex costing that strengthening this guidance. Second, when demand is less dispersed, TVC systems are likely to remain accurate over longer ranges, as firms with a small product portfolio and steady demand may require less complex costing. The results confirm ABC as having superior accuracy; however, it does not draw a new conclusion on why simple TVC systems are frequently applied in practice.

6.4.2 Cost structure modeling

Further disentangling why simple costing is still applied in firms, this section investigates different input resource consumption models using cost structure theory, which concerns the differentiation of cost behavior on specific drivers and measures. For example, cost and production theory state that all costs behave proportionally to demand *q*, which is implicitly used in several studies and models (Anand et al., 2017; Banker & Hughes, 1994; Cooper, 1990). Another classical cost structure differentiation adds non-proportional fixed costs to variable costs. Indeed, the cost structure theory of variable and fixed costs states that fixed costs do not depend on the output of products (Coenenberg, Fischer, & Günther, 2012). ABC advocates claim that cost behavior can be mainly categorized into the unit level (variable costs), batch-level, product-level, and facility-level (Cooper & Kaplan, 1991; Horngren et al., 2014), known as the ABC hierarchy. However, this ABC hierarchy has not yet been confirmed (Anderson & Sedatole, 2013) and the discussion on a suitable cost structure theory is inconclusive.

There is a wide endorsement of ABC structure theory in the literature despite the lack of a closing discussion or empirical foundation for it (Anderson & Sedatole, 2013; Ittner et al., 1997). Abernethy et al. (2001) claim that ABC systems are likely most suitable when batch- and product-level costs reach a certain threshold. This principle holds until today, but cost accounting research continues to discuss its suitability (Anderson & Sedatole, 2013; Ittner et al., 2002; Ittner et al., 1997; Schoute, 2011; Shank & Govindarajan, 1989). Joining the discussion, this thesis seeks to integrate three theories of cost structure to illustrate their sensitivity to and relevance on cost system design choices.

Figure 48 shows formalized cost structure theory at the unit-level, batch-level, and product-level with their formal operationalization, as proposed by Noreen (1991). *Unit-level* processes behave after production output *q*. *Batch-level* processes should be representable by step functions, where *product-level* processes do not depend on *q*. For instance, expenses for processes and for testing product lines are potential product-level costs (i.e. Banker & Hughes, 1994). Product-level costs such as salaries are costs that do not vary by demand, paralleling fixed costs to some extent. By contrast, unit-level costs behave proportionally to demand (i.e., they are actually variable costs). Combing these arguments, there is substantial overlap in the behavior of unit-level and product-level costs as well as variable and fixed costs. Nevertheless, batch-level costs are less clear.

Anand et al. (2019) and Balakrishnan et al. (2011) use negatively correlated minimum input resource requirements λ to model batch-level consumption. After embedding the correlations, Anand et al. (2019) multiply all minimum input resource requirements by realized demand q, whereas Balakrishnan et al. (2011) do not. This differs from cost structure theory, while batch-level processes depend only on batches and not on product units. More interestingly, empirical investigations have found evidence of similarities between unit-level and batch-level costs (Ittner et al., 1997). In detail, Ittner et al. (1997) find that product-level costs are negatively correlated with unit- and batch-level costs, whereas batch- and unit-level costs provide a mixture of positive and negative correlations. When batch-level and unit-level costs are the same, there is less criticism for modeling them distinctively because the drivers make no difference (Babad & Balachandran, 1993; Homburg, 2001).

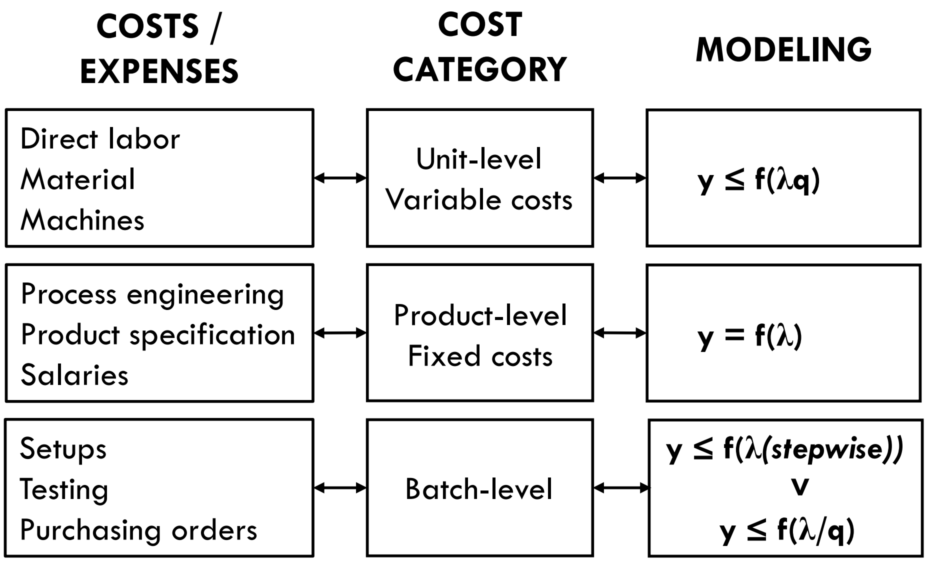


Figure 48: Cost structure modeling

This thesis additionally models batch-level costs in accordance with the economic order quantity model (Misra, 1975) to implement more distinctiveness. Using this to model batch-level costs denominates the costs of batches using products' annual or monthly demand q. The larger demand, the greater the batch size of the product, which lowers the batch-level costs per product unit. For instance, larger batch sizes are associated with less documentation, set-up, testing, and other support activities. Additionally, they may account for some learning and can disperse the costs to more product units. As a result, batch-level activities may have a degressive behavior, and the modeling can use a hyperbola function.

Assume activities' batch-level output y serves as a proxy for a dedicated product batch. The lower overall demand, the larger the batch-level resource consumption of one product. Increasing demand leads to larger batch sizes and this reduces product consumption. Equation (18) expresses the relation between y and q, which is valid until demand becomes too high. Thus, this thesis models batch-level costs using equation (18).

$$\frac{y}{q} \leq f_p(x) \tag{18}$$

The cost structure theory experiment builds upon three theories to investigate their impact on cost measurement. First, MODEL 1 uses the recommendation of unit- and batch-level modeling by Anand et al. (2019). This evidence reflects the empirical findings because this mechanism results in large similarities between the unit and batch-level. Second, MODEL 2 includes the unit-level cost behavior of MODEL 1 but does not multiply the batch-level requirements by demand. This setting ensures negatively correlated resources somehow similar to Balakrishnan et al. (2011). Therefore, batch-level requirements are product-level activities. This thesis interprets this as the classical cost structure with variable and fixed costs consisting of unit-level and product-level costs. MODEL 3 incorporates the renewed batch-level cost modeling plus unit- and product-level activities to introduce the batch-level costs derived from theory.

To sum up, MODEL 1 reflects the unit level and batch-level without negative correlations, as indicated by Ittner et al. (1997). MODEL 2 embeds only the product level because it has a negative correlation with unit-level costs. Therefore, it has distinct unit-level and product-level costs that mirror variable and fixed costs. Finally, MODEL 3 incorporates a subtle ABC hierarchy setting of three distinct activity categories.

The first illustration discretizes cost structure theory using heatmaps (see Figure 49). Figure 49 presents a snapshot of total resource consumption in an average production environment. The heatmaps embody ***RES_CONS_PAT***, where products ***P*** belong to the y-axis and resources ***RC*** to the x-axis. This is indeed a design matrix that maps products' consumption. The left matrix refers to Anand et al. (2019) (MODEL 1,) the second shows the classical variable/fixed cost structure (MODEL 2), and the right one symbolizes the ABC hierarchy (MODEL 3). Every heatmap is a graphic that shows the impact of cost structure modeling on consumption. To sum up, implementing cost structures in the production environment results in distinct patterns of resource consumption.

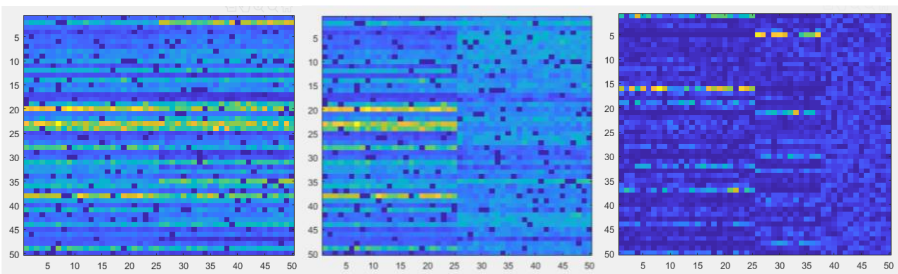


Figure 49: Heatmaps of the total resource consumption of three cost structure models

As shown in Table 17, surprisingly, MODEL 1 has the largest heterogeneity following the measures of Balakrishnan et al. (2011). Table 17 shows the correlations and heterogeneity measures of all the ***RES_CONS_PAT*** in the experiment. There, MODEL 1 has the largest heterogeneity in average consumption distance (20.01/12.93/17.98) in accordance with (Balakrishnan et al., 2011). Looking at the product characteristics, conversely, the picture shifts. MODEL 1 has the largest *INTER*=215, where MODEL 3 has the most extensive *INTRA*=0.48. Interestingly, MODEL 2 is similar to MODEL 3 in terms of *INTRA* but has less *INTER*. Hence, rich cost structures are close to the products' heterogeneity.

Table 17: Average descriptive statistics for the implications of cost structure modeling

Descriptive Measure	**Unit**	**MODEL 1** **Unit** **Batch**[1]	**MODEL 2** **Variable** **Fix**[2]	**MODEL 3** **Unit** **Batch**[3] **Product**
Correlation between elements				
Average correlation between unit- and batch-level consumption	[#]	0.00	0.00	-0.12
Standard deviation of the between unit- and batch-levels	[#]	0.15	0.15	0.11
Average correlation of the between unit and production volume	[#]	0.54	0.54	0.45
Density [*DENS*] of resource consumption matrix				
Percentage of zero entries in the consumption matrix	[%]	45.02	45.02	45.02
Average number of products consuming a resource	[#](max=50)	27.49	27.49	27.49
Average range in the consumption of a resource across products	[%]	20.01	12.93	17.98
Heterogeneity within the portfolio [*INTER* / *INTRA*]				
Average |*INTER*|	[#]	215	140	201
Average |*INTRA*|	[#]	75	90	145
Standard deviation of *INTER* within a product portfolio as a percentage	[%]	2.65	2.25	1.84
Standard deviation of *INTRA* within a product portfolio as a percentage	[%]	0.31	0.45	0.48

[1] Batch-level modeling following Anand et al. (2019).
[2] Batch-level modeling following Anand et al. (2019) without demand *q* multiplication that leads to product-level modeling. This scenario comes closest to traditional cost structure theory of variable/fixed costs).
[3] Batch-level modeling after a hyperbola function.

To sum up, cost structure modeling determines heterogeneity in the production environment. The cost structure theory of the ABC hierarchy is expected to be relevant for making effective cost design choices. Unfortunately, it has not yet been fully modeled or confirmed, and research uses the underlying framework in various settings to link value chain processes with costs (Park & Simpson, 2008; Thyssen et al., 2006). Hence, the reported descriptive statistics show the impact of the smallest variations in resource modeling, with the subsequent experiments demonstrating how they affect an error assessment and may adjust qualitative interpretations.

6.4.3 Evaluating the impact of cost structure theory

The next experiment incorporates the three above-described cost structure theories. Every cost structure treatment is implemented and costs are measured in the same experimental setting. The experimental design in Table 18 is comparable to the experiment between complex ABC and simple TVC systems (see Section 6.4.1); however, different input resource consumption modeling is used in this case.

Table 18: Experimental design – Cost structure modeling

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,0.6,0.85]	Products	50	Euclidean distance [EUCD€]
Q_VAR	[0.5,1,1.5]	Activities	50	
RC_VAR	[0.4,RND,0.7]	Resources	50	
UNIT_SHARE	[0.3,0.5,0.7]	Repetitions	20	
COR	[-0.6,0,0.6]	Total costs	1,000,000€	
ERROR	[0]	ABC(CPH)	*Correl-Random*	
CP	[1,2,4,6,8,10]	ABC(CDH)	*Big pool*	
MODEL	**[1,2,3]**			
n= 29,160 ($3^5 \cdot 6 \cdot 20$)				

Figure 50 demonstrates the three outcomes of the same experiment under different cost structure theories. Interestingly, there is no qualitative difference in the marginal efficiency of complex ABC systems. Around 10 cost pools are required before ABC shows diminishing marginal efficiency. The reported results confirm the suggested guidance of Balakrishnan et al. (2011). The experiment is thus a valuable example of changing central elements to understand and substantiate mechanisms (Thiele & Grimm, 2015).

Figure 50 also shows that TVC is more efficient in MODEL 1 despite batch-level costs, whereas the ABC system with 10 cost pools cannot outperform TVC. This result is surprising because it entirely contrasts guidance and theory. When MODEL 1 reflects today's realistic environment, complex costing does not easily outperform TVC. MODEL 2 and MODEL 3, conversely, show the expected horserace, where the TVC system quickly loses accuracy compared with complex ABC systems. Consequently, this thesis concludes that MODEL 1 is a fruitful scenario for TVC despite batch-level costs in contrast to all previous guidance (Abernethy et al., 2001; Cooper, 1990; Cooper & Kaplan, 1998b; Drury, 2015; Horngren et al., 2014; Ittner et al., 1997).

Another result arises from the observation of no qualitative differences between MODEL 2 and MODEL 3, which questions the superiority of the ABC hierarchy over classical cost structure theory with variable and fixed costs. Textbooks and ABC advocates have promoted that the ABC hierarchy outperforms the classical perspective by supporting more granular information (Cooper, 1990; Cooper & Kaplan, 1998a, 1998b). Interestingly, this result is not fully depictable in the experiment because the outcome between a simple variable and fixed cost structure is somewhat comparable. Although there is a small quantitative offset between both, there is less qualitative difference in behavior.

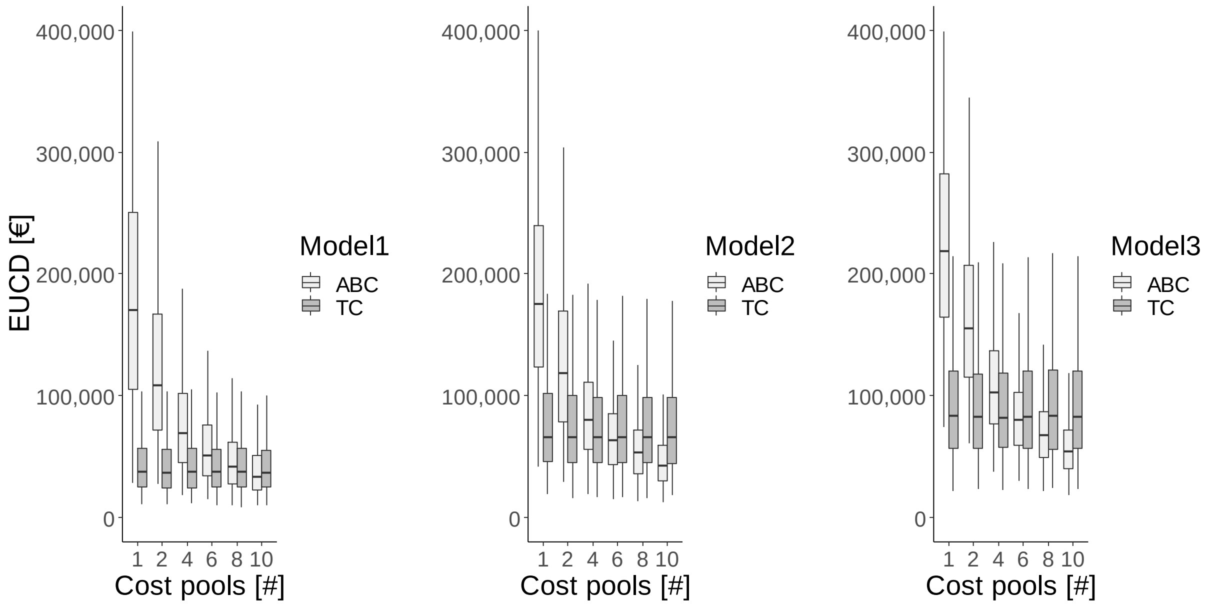


Figure 50: TVC vs. ABC experiment under different cost structure theories

Summarized, cost structure theory decisively affects the advantage and usability of complex ABC systems, with this thesis finding no clear evidence for the superiority of the ABC hierarchy or that TVC is less efficient among batch-level costs. The ABC hierarchy shows the need for hierarchical cost drivers and prompts the acknowledgment of many cost drivers and expenses. The experiments provide the first quantitative results on the application of a hierarchical cost structure, particularly to unit-, batch-, and product-level costs. The reported results also show that complex cost structures demand complex ABC systems, but this is also observable when adopting a variable and fixed cost (i.e., classical) structure. Further, TVC is more efficient than expected, even though batch-level costs exist. Therefore, product-level costs are rather the focus, which are similar to fixed costs. Overall, the reported results confirm that complex ABC systems are more suitable for complex cost structures but find that the classical perspective of variable and fixed cost is sufficient. Finally, the series of experiments identify a potential scenario where complex ABC systems do not necessarily outperform simple TVC systems.

6.5 Examining the impact of direct costs

6.5.1 Reviewing direct costs

Little attention has been paid to the role of direct costs in costing systems, probably due to their error-free nature in contrast to overhead cost allocations. Direct costs account for a substantial share of firms' costs and new information technology capabilities are likely to shift the balance toward direct costs even more (Kache & Seuring, 2017; Matthias, Fouweather, Gregory, & Vernon, 2017). Nonetheless, although the growth in information technologies may affect product cost measurement, this issue is under-studied in cost accounting research. To anticipate the consequences of increasing direct costs, this subsection thus investigates their impact on accuracy.

In costing systems, direct costs are directly traceable to their causing objects, whereas indirect costs are still entangled and need further allocation. Table 19 provides an extended literature review of the specific cost share (Fixson (2006) was the first to provide an overview of this topic). Direct costs frequently have a share greater than indirect costs. By contrast, some sectors such as finance and services have more considerable indirect costs as well as around 50% direct costs.

Table 19: Studies that have accounted for the share of direct costs

Reference	Total costs [100%]				Additional information
	Direct costs		Indirect costs		
	Material	Labor	Unit level (MOH)	Non-unit level (NMOH)	Sample size [n] Industries considered Further comments
Miller and Vollmann (1985)	20-40		60-80	-	N= n.a. Electronics firms
Foster and Gupta (1990)	54.3	6.6	39.1	-	N= 37 Facilities of a large electronics company (only total manufacturing costs)
Galsworth (1994)	40-65	35-60	-	-	Lacking clarity
Banker et al. (1995)[1]	65.4	8.9	25.7	-	N= 32 Electronics, machinery, and automobile (only total manufacturing costs)
Hundal (1997)	50-60	10	20-30	-	N= 7 Automobile, computers, general manufacturer (only total manufacturing costs)-
Al-Omiri and Drury (2007)[2]	52.2	14	10.3	14.8	N= 86 Comprehensive sample 8.7% direct non-manufacturing costs
Kallunki and Silvola (2008)[1,2]	32.7	33.2	9.4	14.6	N= 105 Trade, service, media, metal industry 10.10% direct non-manufacturing costs
Average	70		30		

[1] All descriptive values were averaged over the life cycle phases to approximate an estimate. Afterward, all values were normalized to 100% of total costs.
[2] Both studies incorporated the category "other direct manufacturing costs" listed in the comments.

Direct costs are known to be error-free (Labro & Vanhoucke, 2007, 2008) and remain little discussed in cost accounting research. Recall that cost accounting has predominantly investigated accuracy-related questions to improve product cost-based decisions. When assuming perfect direct costs, there is only a question of the errors in overheads. Looking at it from this angle, the abstraction in cost accounting is theoretically valid.

Concerning the impact of product cost errors, absolute measures such as the *EUCD* may underestimate cost errors under direct costs, whereas *PE* and *APE* provide a more accurate view. Products with a large share of direct costs suffer less from erroneous overheads from a relative perspective (*PE* and *APE*). Monetary error metrics as the *EUCD* should remain constant. However, the magnitude and impacts change as *PE* changes. Overall, one can presume that classical overhead cost allocation loses relevance as direct costs increase (Zimmerman, 1979).

6.5.2 Direct cost modeling

This thesis assumes that increasing information technology capabilities leads to higher shares of direct costs through more detailed data on products' resource usage. To establish and ground the hypothesis, this thesis uses studies that have explored the empirical cost literature but only found marginal evidence. In detail, no empirical study has thus far hypothesized that increasing information technologies increase the share of direct costs. That said, Al-Omiri and Drury (2007) find a large but non-significant correlation of -0.098 between information technology quality and the average percentage of indirect costs, which may substantiate the presumed positive relationship between information technology and the direct cost share.

Analytical/numerical studies model direct costs as exogenous and have not explicitly considered their impact on costing errors (Christensen & Demski, 1997, 2003). Analytical research exclusively determines costs *a priori* into overheads and direct costs. Although this is valid for several investigations, the impact of direct costs is not well understood. Further, analytical studies have used relative percentage errors such as *PE* and *MPE*, which are more responsive to the share of direct costs.

Lastly, production and cost theory do not differentiate between direct and indirect costs, which is a cost accounting issue. Consequently, using full information as a benchmark costing system is a full direct cost scenario. Distancing from this ideal situation because of limited information, some direct costs are overheads and vice versa. Therefore, the used costing benchmarks are complete direct cost scenarios in which a lack of information shifts them to overheads.

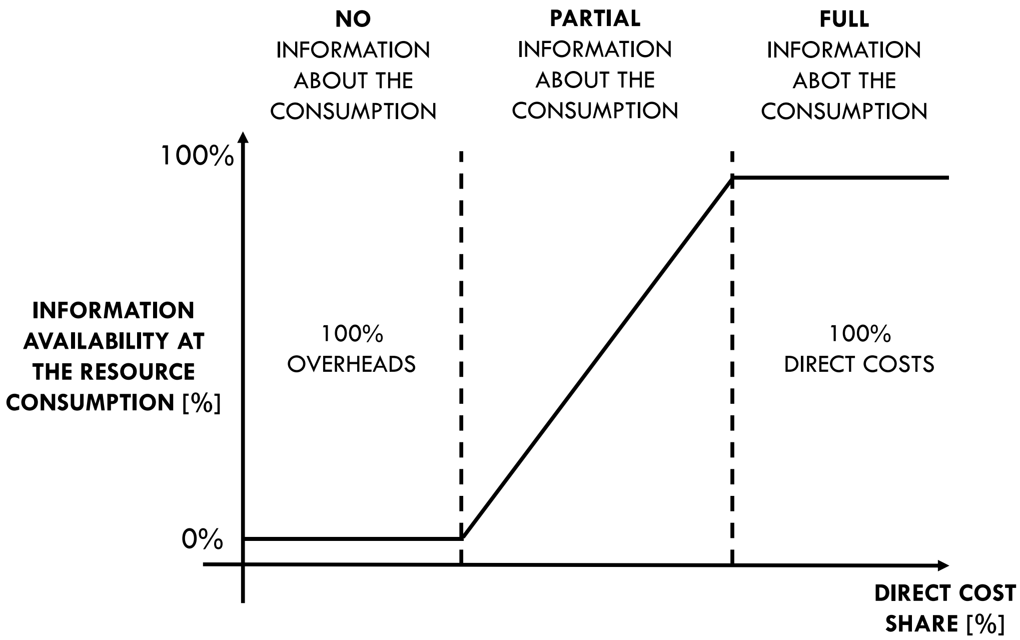


Figure 51: The impact of information availability on the share of direct costs

The previous argumentation supports the conceptualization of Figure 51 that models the share of direct costs in accordance with the availability of information on process and resource consumption. The conceptualization includes three phases. First, having *no information* about firms' resource consumption leads to one *RCC*, including all kinds of costs. This situation is ideal when firms have at least some information. This leads to the second area with increased information availability. Having *limited* information on resource consumption patterns yields a partial decomposition into overheads and direct costs, as frequently observed in practice.[46] Finally, the ideal condition of information is that there are no overheads; this results in a full costing benchmark.

Table 20: Experimental design – Direct cost experiment

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,RND, 0.85]	Products	50	Euclidean distance [EUCD€]
Q_VAR	[0.5,RND, 1.5]	Processes	50	Mean percentage error [MPE%]
RC_VAR	[0.4,RND,0.7]	Resources	50	
UNIT_SHARE	[0.3,RND,0.7]	Repetitions	100	
COR	[-0.6,0,0.6]	Overheads	1,000,000€	
ERROR	[0.1,0.3,0.5]	TVC(CPH)	Random	
CP	[1,2,4,6,8,10]	TVC(CDH)	DIV	
DC_SHARE	[0.2,0.4,0.6,0.8]	ABC(CPH)	Correl-Size	
		ABC(CDH)	Big pool	
n= 16,500 ($3^2 \cdot 6 \cdot 6 \cdot 50$)				

6.5.3 Evaluating the share of direct costs

The analysis pursues the suggested direct cost modeling and examines different levels of direct cost shares *DC_SHARE* by observing their resulting errors. Staying in the horserace scenario between TVC and ABC, the investigations confirm that the *EUCD* does not change under constant overheads. The MPE conversely shows – as expected – the impact of the percentage errors.

As introduced, direct costs are not predestined and depend on information technology. As such, this thesis differentiates between direct $\boldsymbol{RCC^{DC}}$ and overhead costs $\boldsymbol{RCC^{OH}}$ instead of assuming generic resource costs ***RCC***. The computerized model uses 50 $\boldsymbol{RCC^{OH}}$ and 50 $\boldsymbol{RCC^{DC}}$, where *DC_SHARE* regulates the total costs of the firm. Both costs lead to the final product costs under the existing resource consumption pattern. Next, the computerized model fixes 1,000,000€ to $\boldsymbol{RCC^{OH}}$ and increases the number of direct costs under *DC_SHARE*. For instance, given the level of 0.6, *DC_SHARE* calculates total costs of 2,500,000 TC from (sum($\boldsymbol{RCC^{OH}}$)/(1-*DC_SHARE*)). The additional 1,500,000€ is hence direct $\boldsymbol{RCC^{DC}}$, yielding 40% overheads and 60% direct costs.

Figure 52 demonstrates and substantiates the previous intuition about the error metrics because the EUCD does not differ among levels of *DC_SHARE* as *MPE* shrinks. As can be seen, there is less congruence between the EUCD and MPE, while the latter indeed profits from fewer overheads in the system. Another interesting artifact is that for a *DC_SHARE* of 60%, the MPE of TVC is 14.47% and 8.90% for ABC with 10 cost pools (Δ 5.57%). The difference at an 80% *DC_SHARE* is smaller by about Δ3.14% (7.90% - 4.76%). Conclusively, this thesis reports evidence that the superior advantage of ABC

[46] For example, where consumption of material and labor is more observable referring to their strict proportionality to demand, indirect support processes have fewer clear consumptions. In particular, dispositive input resources (i.e., administrative, engineering, or development processes) are more latent (Park & Simpson, 2008).

systems over simple costing systems differs only to a small extent when the direct cost share is increasing. An untabulated regression model predicts that TVC is more responsive to increasing *DC_SHARE* than ABC systems. In detail, the linear ordinary least squares regression model reveals that the standardized regression coefficient B(*DC_SHARE*) is 0.89 for TVC and 0.56 for ABC in terms of the MPE. Additionally, η^2 is 0.79 for TVC and 0.31 for ABC. Hence, TVC may profit more from increasing direct costs, but this effect is too small to change the final outcome.

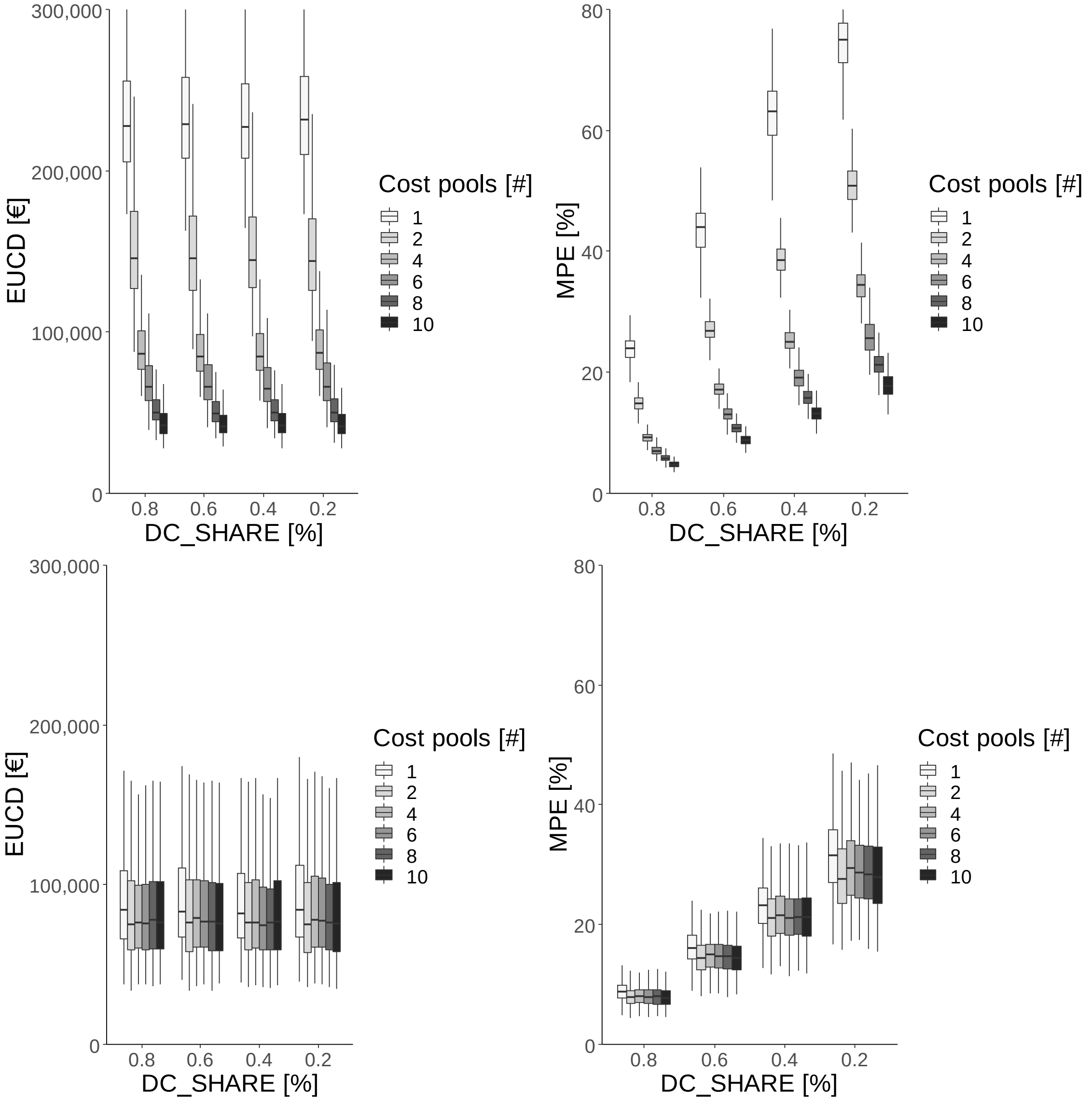


Figure 52: Results of increasing direct costs in ABC (upper panel set) and TVC (lower panel set)

The remaining question is how large the relative errors are at a high *DC_SHARE*. There has been no guidance about over- and undercosting under the influence of direct costs. In particular, the product level is decisive for evaluating the quality of the cost information used by decision-makers. In this respect, Table 21 applies the materialistic ±5% rule from Kaplan and Anderson (2007) and reports average probabilities being either over- or undercosted. Increasing direct costs from 20% to 80% reduces over- and undercosting from Σ 83.29% to Σ 35.29% in an ABC system on average. This is a remarkable difference of 48%; nevertheless, Σ 35.29% are still being over- and undercosted. A side observation is that TVC tends to be less overcosted than ABC on average (Δ -2.84%). The experiment overcomes this point by demonstrating that simple costing may overcost a few products to a large extent (i.e., *DC_SHARE*=0.8 | Δ -6.44%) and persistently undercost. This thesis thus concludes that over- and undercosting are present even though the direct cost share is increasing.

Table 21: Over- and undercosting among varying levels of *DC_SHARE*

Products' average probability of being over- and undercosted ±5%						
Costing system	**Unit**	**Global average**	**Percentage of direct costs [%]**			
			20	**40**	**60**	**80**
TVC CP=1	Overcosted [%]	24.11	28.50	26.34	23.81	17.72
	Undercosted [%]	52.77	61.16	59.50	53.77	36.66
	Overall [%]	76.88	89.66	85.84	77.58	54.38
ABC CP=10	Overcosted [%]	26.69	34.94	31.95	25.96	14.99
	Undercosted [%]	38.17	48.35	45.29	38.74	20.30
	Overall [%]	64.86	83.29	77.24	64.70	35.29
Δ (TVC – ABC)	Δ Overcosted [%]	-2.84	-6.44	-5.61	-2.15	2.83
	Δ Undercosted [%]	14.60	12.81	14.21	15.03	16.36

The next experiment concerns the question of increasing information technology in an existing production environment. Figure 53 demonstrates an ongoing transition from full overheads to direct costs, where firms can randomly select the direct costs, or do so based on their size. This experiment focuses on the availability of direct costs to address random or size-based availability. For instance, firms may have high direct costs such as material and labor, whereas other costs are less tangible and likely be overheads. Thus, higher resource costs are more likely to be direct under the size-based approach. By contrast, the random approach uniformly chooses a firm's direct costs. Interestingly, the last 30% of the costs under the size-based approach are responsible for an MPE of 18.65% compared with 13.30% under the random approach. Additionally, the right panel in Figure 53 has a slightly concave shape. As a result, this thesis concludes that firms should not necessarily focus on reducing their most considerable resource costs, as less focus may support costing as well.

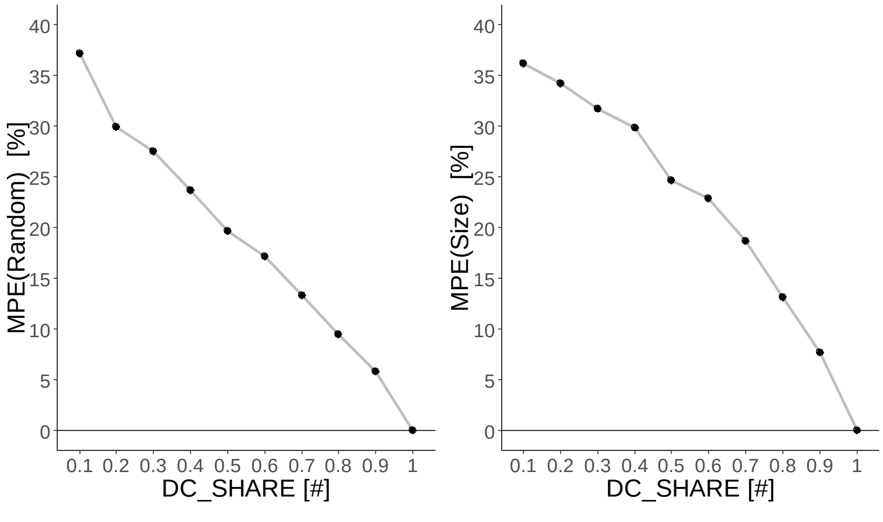


Figure 53: Increasing the direct cost share (*DC_SHARE*) and impact on the MPE (left panel: randomly chosen, right panel: size-based approach)

To sum up, the direct cost experiment reports that even large shares of direct costs do not outweigh the overhead allocation. Of course, the overall error will decrease; however, approximately 30% of products in the portfolio remain over- or undercosted under a recommended ABC system. This result is unexpected because more excellent information technology capabilities should overcome this. Overall, this thesis discussed direct cost shares and provided the insight that even fewer overheads may play a vital role in cost-based decision-making.

6.6 Contribution

This section contributes to the discussion of cost system design choices as follows.

Simple product costing

This thesis contributes to cost design theory by emphasizing the cost driver selection as decisive for simple TVC systems, in particular, because aggregated cost drivers are less distorting. Cause-and-effect drivers are assumed to be preferable to the *cause-and-effect criterion* for selecting cost drivers (Horngren et al., 2014, p. 108) regardless of whether simple or complex costing systems are used. The series of experiments introduces aggregated cost drivers such as production volume and direct labor hours as an efficient alternative to cause-and-effect cost drivers in simple costing systems. In detail, aggregated volume-based allocations outperform certain cause-and-effect drivers. This superiority of aggregated costing parallels the economic analysis of Feltham (1977), who analytically demonstrates that aggregation loss can be rather small when drivers consist of sums or averages. It is reasonable that cause-and-effect drivers perform worse in solving large specification problems in contrast to aggregation losses as simple cost drivers. Finally, this thesis finds that the *cause-and-effect criterion* is not a general rule of thumb and should be primarily used when applying complex product costing systems.

Cross-subsidization

Second, this thesis contributes to *cost (error) behaviors* (Krishnan, 2015) by disentangling the error drivers of classical cross-subsidization in a large-scale setting. There is known guidance (Cooper & Kaplan, 1988; Shank & Govindarajan, 1988) that complex, less unit-level activity-consuming products are undercosted, whereas simple, large unit-level activity-consuming products are overcosted (Drury, 2015; Horngren et al., 2014). However, this thesis substantiates and clarifies the drivers further. Product units are still the best indicator for approximating over- and undercosting in TVC systems. Although undercosting is dominant in product portfolios, overcosting is not fully predictable because of simplicity and mass production. The general tendencies of simple and complex products in terms of over- and undercosting are seemingly unsustainable according to the numerical exploration. To be concise, costing errors behaves oppositely as suggested, while *simple* products with large volumes may be less overcosted and rather accurate. *Complex* products with transactions and large output, conversely, are overcosted. Overall, cross-subsidization is still present, but mainly for complex products with unit-level activity consumption.

The horserace between ABC and TVC

Concerning the cost system design of simple TVC and complex ABC systems, the ABC system has performance advantages. To explain this issue further, this thesis first substantiates that cost structures do not necessarily emphasize the need for complex costing in terms of its higher accuracy and that the traditional classification of variable and fixed costs may be sufficient for choosing a cost system design. Of course, it is understood that fixed costs need more complex costing systems; however, this distinction has blurred because Cooper and Kaplan (1987) claim that there are no fixed costs while highlighting the ABC hierarchy. Thus, complex product costing such as ABC is necessary when batch- and product-level costs are high (Abernethy et al., 2001; Horngren et al., 2014; Schoute, 2011). The performed experiments suggest, conversely, that the ABC hierarchy does not lead to a different design choice than traditional cost structure theory for supporting cost design choices. Thus, combining the non-findings from empirical ABC hierarchy studies and the less distinctive pattern from the experiment, the ABC hierarchy is likely to overspecify firms' underlying cost structure. Another result arises from the performance of the TVC system despite batch-level costs, which questions previous guidance further. The experiment uses the resource modeling standard of Anand et al. (2019). Surprisingly, simple TVC systems outperform complex ABC systems over a long range, suggesting that batch-level costs are not decisive for selecting a cost system design. Overall, this thesis thus questions cost system design guidance on batch-level costs and calls for more empirical research.

Direct costs

Increasing information technology improves the capabilities of disentangling consumption within production environments that increase direct costs. Empirical studies have lacked a robust discussion on whether increasing information availability raises direct costs or whether direct costs affect the cost system design choice. First, this thesis finds evidence on the proposition that simple costing systems profit more than complex ABC systems from having a large direct cost share. Nevertheless, this effect does not help them outperform complex ABC systems. A more remarkable finding is that errors in the product costs remain despite large direct cost shares. In sum, this thesis confirms the need for cost allocation even though the magnitudes of errors decrease with increasing information capabilities.

7. Bias and Imprecision of Product Costs

7.1 Introduction

This section applies general measurement theory to cost accounting systems to determine inaccurate cost information as a construct of bias and imprecision. Like all measurement systems, costing systems contain measurement errors question the validity and reliability of measurands. Measurement theory seeks to identify and describe both the quality aspects of measurement and models' errors further. Although both simplified and aggregated costing systems have systematic errors, more complex systems are prone to uncontrollable random measurement errors (Mertens & Meyer, 2018). While systematic errors result in a shift called bias, random errors manifest as a lack of precision, called imprecision. It is thus reasonable that all measurement errors propagate through costing systems toward product costs, where measurement theory provides the necessary calculations. As a result, information quality depends on the magnitude of bias and imprecision referring to measurement theory, which may affect cost-based decision-making (Balakrishnan et al., 2012a).

The research examines the accuracy of costing systems (Balakrishnan et al., 2011; Homburg et al., 2017; Hoozée & Hansen, 2018; Hoozée et al., 2012); however, less research has investigated the variance in errors. Although a lack of precision is vital in all kinds of accounting values (Banker & Datar, 1989; Christensen, 2010; Erb & Pelger, 2015; IASB, 2018), most studies overlook the topic. In particular, the usage of erroneous cost information suggests that managers can make false rankings, comparisons, and evaluations (Demski, 2008) that may lead to negative economic consequences from cost-based decision-making.

This section hence is devoted to the quality aspect of bias and imprecision in cost information because it is decisive for decision-making and reporting (IASB, 2018). This study departs from previous work because it uses the calculations of measurement theory frequently applied in engineering and natural science in management accounting systems. Despite being a non-standard approach, this thesis takes advantage of this perspective to show the bigger picture of bias and imprecision. To do this, this section also accounts for numerical explorations because repeated measurement is necessary to recognize the weight of imprecision. Afterward, product costs are no longer seen as reliable estimates but as having an error range. This leads to new questions about decision-making because imprecision hampers the evaluation of optimal performance and pricing. Ultimately, this thesis performs a sensitivity analysis to identify cost error behaviors and thus explain both quality dimensions of measured information.

7.2 The bigger picture on errors

7.2.1 Principles of measurement theory

The principles of measurement theory do not exclusively apply to engineering and natural sciences; this thesis sees the theory as necessary for monetary and behavioral systems, too. Applying it to (management) accounting information systems provides guidance on the calculations needed to offer an accurate picture. Knowledge of management disciplines and dissimilar terminology about measurement concepts and error modeling is limited (Amershi et al., 1990; Dikolli & Sedatole, 2007; Merchant & Shields, 1993). Even the IASB (2018) has changed its definition of reliability over time. Accepting measurement theory instead gives explicit guidance on error modeling that supports the measurement of erroneous accounting information.[47]

A measurement system contains a design of measurement functions *m* that uses quantifiable inputs *x* to approximate an output value of the intended measurand *y* (JCGM, 2008). Measurement functions capture physical attributes to assign quantitative variables to the characteristics of an intended output object *y*. This is the most common measurement approach because measurands are rarely directly observable (DIN1319-1, 1995-01) and hence require indirect measures to carry out the subsequent calculations to better approximate the intended measurand (Puente León, 2015). Equation (19) introduces the measurement system *m* employing a design and *k* measurable inputs *x* with calculations to approximate the measurand *y* (Grabe, 2014; JCGM, 2008).

$$y = m(x_1, x_2, \dots, x_k) \tag{19}$$

Indirect measurable inputs *x* are seldom error-free because erroneous measurement processes produce estimates $\hat{x}$ including errors e_x. All inputs are somehow superimposed by errors, for instance, from white noise.[48] Therefore, the measured input values are estimates $\hat{x}$ with a measurement error *e* consisting of bias and imprecision. The error next propagates to the final measurand and this transfers it to an estimate $\hat{y}$, too. This updates equation (19) to a more realistic measurement system (20).

$$\hat{y} = m(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_k) \tag{20}$$

Knowing about imperfect measurement implies doubts about which measurement theory tries to quantify an underlying error uncertainty. Measurement theory is differentiated into systematic and random based on their specific behavior and nature. Systematic errors are due to causal reasons and induce a constant shift between the "true" measurand y and measurand estimate $\hat{y}$. The deviation is

[47] In detail, IASB (2018) claims that "the level of uncertainty involved in estimating a measure of an asset or liability may be so high that it may be questionable whether the estimate would provide a sufficiently faithful representation", which is comparable to large imprecision. The IASB (2018) has a clear understanding of useful information. For example, when one is unable to recognize uncertain measures, using other measures may be more appropriate, paralleling the points of Christensen (2010).

[48] There is no substantial difference between error and deviation (DIN1319-1, 1995-01).

known as bias. Random measurement errors are entirely uncontrollable and do not follow any systematic pattern. Recognizing the controllable nature is solved by repeating measurements to account for the errors in a distribution, namely imprecision.[49]

Figure 54 illustrates the outcome of the measurand from a repeated measurement process adopted to approximate bias and imprecision. The gray-shaded normal distribution indicates the dispersion when performing repeated measurements. As explained, the measure is uncontrolled regarding random measurement errors. The resulting average is the measurand estimate $\hat{y}$ and this is the most counted measurement in the repetitions. The difference between the "true" value and estimate is recognized as the bias.

In greater detail, the random measurement errors superimpose the estimate, which indicates the range and interval of imprecision. This imprecision accounts for the variance in errors, where research employs multiple standard deviations when assuming an ideal normal distribution. To indicate a 95% interval, imprecision is operationalized as ±2σ. Figure 54 illustrates imprecision as an error range, which can be either positive or negative (**±)**.

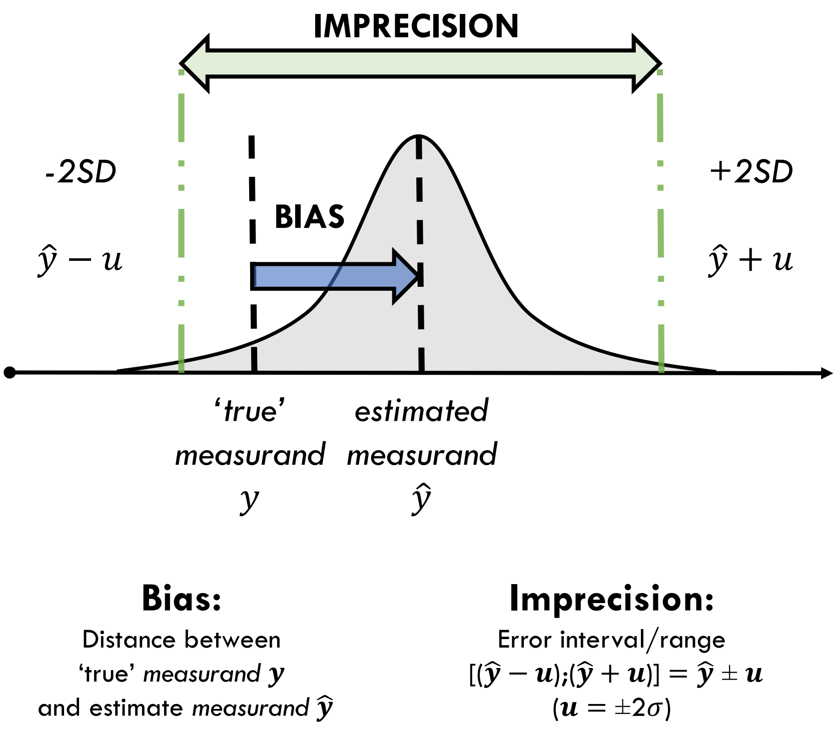


Figure 54: Measurement theory consisting of bias and imprecision

Overall, measurement theory offers an operationalization for calculating bias and imprecision from erroneous measurement processes. Systematic errors are controllable and persistent over repeated measures, where the recurring distance between the "true" value and estimator is the bias. Random errors are uncontrollable and not causal. They can randomly change their magnitude and direction with each

[49] There are different scales for describing a probability interval. Measurement theory mainly uses multiple standard deviations referring to the expectations of the community (i.e., ±2σ or ±7σ).

measurement. As a result, random errors manifest around the estimate as a probability indicating a possible error range called imprecision.

7.2.2 Measurement theory in cost accounting

Aggregation, specification, and measurement errors are typical error causes in cost accounting, and measurement theory can parallel them using systematic and random errors. The theory around the error cause typology does not support calculating the error types in product costs. Therefore, this thesis bridges the gap between modern cost accounting theory and the principles of measurement theory to discuss error types that occur in cost information, particularly concerning imprecision. This is valuable because it reflects the errors in final product costs and evaluates them according to accounting standards (FASB, 2010; IAASB, 2008; IASB, 2018). This shifts, at least partially, the perspective from designing an effective cost system to the quality of cost information for influencing decision-making. Overall, adapting measurement theory to evaluate the errors in cost information may be the first step toward systematizing and elucidating the errors of all (measurement) accounting systems.

A cost (measurement) system uses resource consumption or other aggregated measures from production technology as indirect measurable input quantities x to allocate overheads to products. The first process is to measure resource and activity measures (i.e., machine hours, number of setups) to obtain the input quantities. Then, the inputs will allocate the costs from the cost pools. Overall, a costing system is a measurement system that uses the underlying production technology to measure physical units for tracing and allocating costs.

Less alignment to the production technology leads to *systematic* distortions in terms of specification and aggregation errors. The specification error of Datar and Gupta (1994) indicates the wrong choice of an allocation base (i.e., selecting $\hat{x}$ instead of x). For example, using the energy consumption of a machine to allocate its depreciation costs may not fully reflect the underlying resource consumption. Aggregation errors result from grouping heterogeneous resources or activities and therefore neglecting information ($\sum(x_1, x_2) = x_{1,2} = \hat{x}$). For example, grouping marketing and operations is problematic because they do not have the same underlying production functions. Such aggregations lead to errors and subsequently hamper the correct specification of drivers. Thus, both will interact and worsen the accuracy of a cost system design.

Further, both tend to depend on the initial cost system design choice and thus the costing system. Assuming the emergence of specification and aggregation in the cost system design process, both will be wrong and may imply a systematic error. The other error cause in cost system design relies on random measurement errors that arise in various ways. Examples in cost accounting are time misestimations (Cardinaels & Labro, 2008), process stochasticities such as congestion or deficient products (Banker, Datar, & Kekre, 1988), false master data (Mertens & Meyer, 2018), and even the manipulation of employees (Weber, 2005). As a result, the measure used to allocate overheads does not reflect "true" resource consumption.[50]

To sum up, while aggregation and specification errors persist in a costing system, random measurement errors are uncontrollable and can change in each measurement. Measurement errors do not persist in a costing system and change in each measurement period. Aggregation and specification errors are due to less specified cost measurement systems or wrongly chosen drivers. Although these errors can fluctuate, there is less demand for continuous cost system design updates in practice. Therefore, this thesis suggests that aggregation and specification systematically distort cost information through biases, where random measurement errors are responsible for imprecision.

Figure 55 conceptualizes the augmented relations in the context of measurement theory and cost accounting similar to extrapolating bias and imprecision as the drivers of validity and reliability. The terminology in the literature is not always consistent, as validity and reliability are often used in empirical research to assess construct reliability and validity (McKinnon, 1988). In accounting, by contrast, faithful representation and relevance are dominant qualities in the recognition process (IASB, 2018). In particular, faithful representation concerns measurement uncertainty in terms of validity and reliability, which leads to accurate measurement.

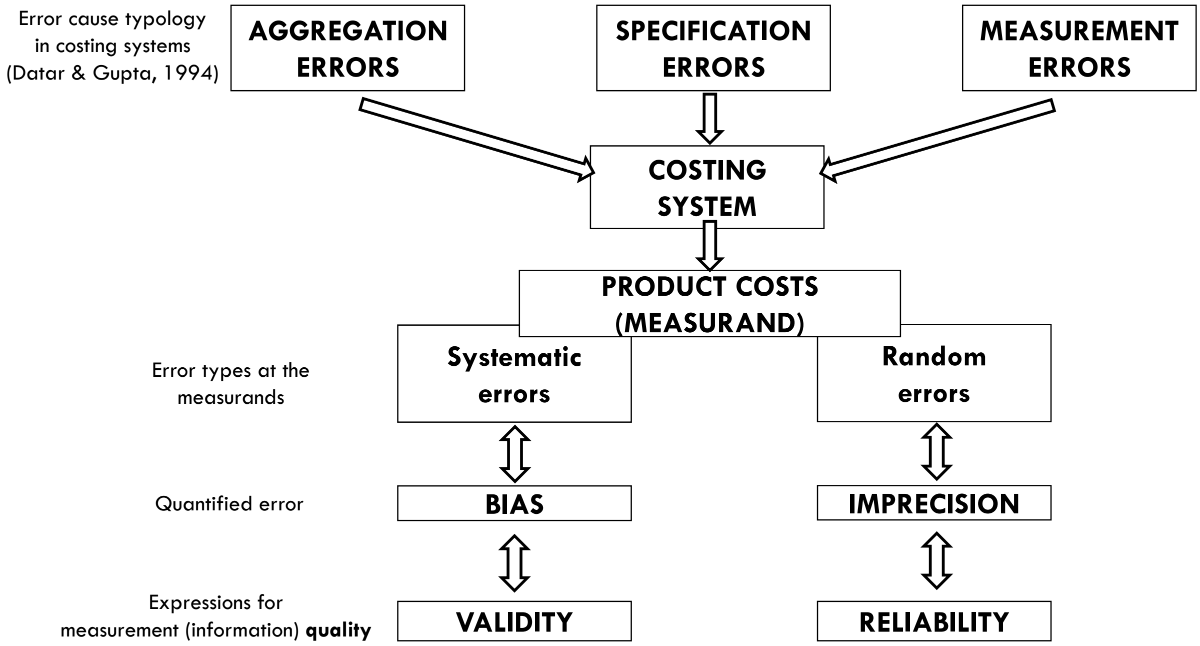


Figure 55: Bridging cost error causes with measurement theory

[50] Concerning single measurement studies (Labro & Vanhoucke, 2007, 2008), there is no distinction between measurement and specification errors. However, concerning repeated measurement, there is a disparity. Imagine that a specification error means the selection of the wrong allocation base. When selecting the wrong base, it may exist more than one period in contrast to random one-time measurement errors.

Among the last steps, the question of inaccurate or accurate measurements relates to the degree of bias and imprecision, as shown in Figure 56. Primarily, all four targets can contain a “true” value with multiple measurements. Figure 56 demonstrates the common accurate measurement metaphor for describing and showing the context of inaccuracy and accuracy, illustrating the quality of cost information according to Mertens and Meyer (2018). This illustration depicts the quality of the measured information by demonstrating bias and imprecision in multiple measurements. At least one of the error quality dimensions is seemingly relevant for increasing the degree of inaccuracy. This thesis thus suggests that using accurate product costs is associated with the bigger picture of bias and imprecision errors.

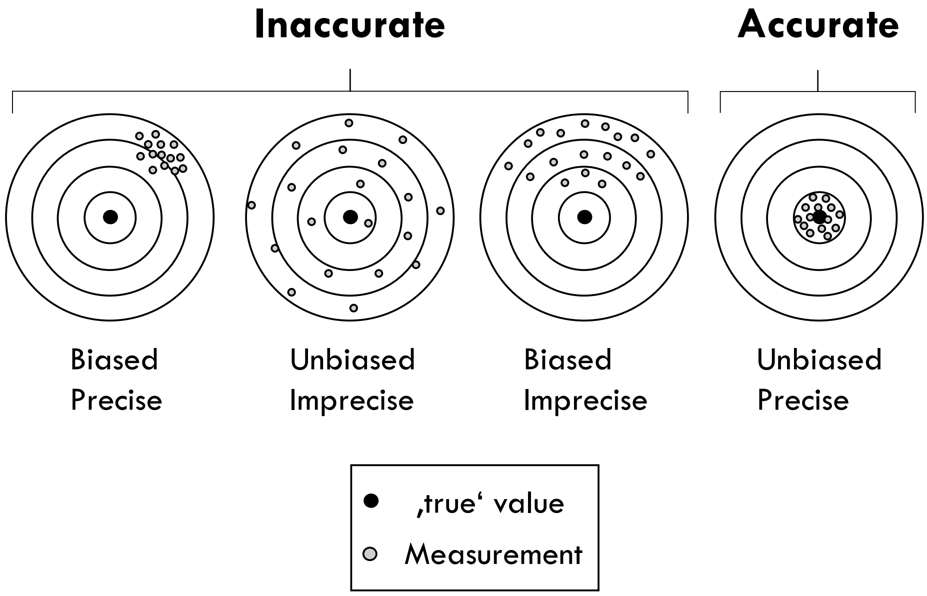


Figure 56: Conceptual overview of inaccurate and accurate measures (Mertens & Meyer, 2018)

7.3 Model design concept

Measuring the imprecision of each product cost demands repeated measurements using the same measurement system in a production environment. The model design concept does not branch into conceptual and computational types because the computational model is the same as that in Section 6.2.2. The model rather generates a production technology in accordance with previous settings and under constant demand, which secures the invariant resource consumption setting and thus yields the benchmark product costs. Instead of adopting a single measurement as in the previous section, the model applies a specific number of repeated measurements, which allows random measurement errors to vary. Although costing systems cannot do this in practice, they can analyze imprecision in product costs to calculate the bias and imprecision of a product cost value. Figure 57 visualizes this walkthrough for one numerical run, where the dashed lines highlight the repetition (see the numerical example in Section 10.3 for further details).

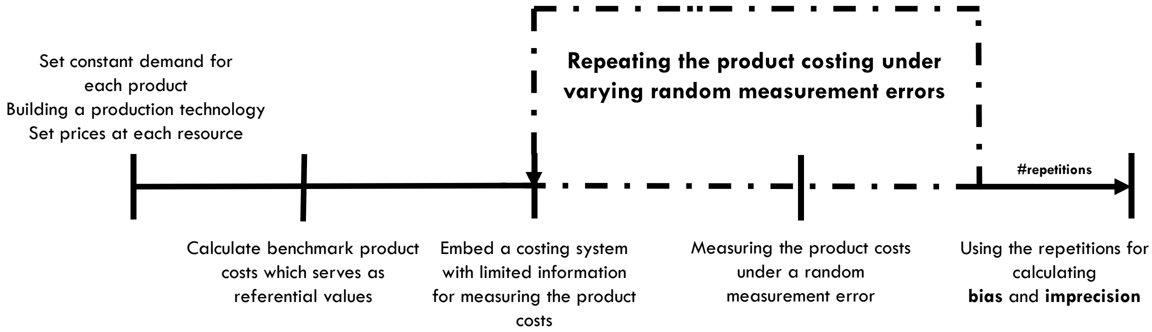


Figure 57: Conceptual walkthrough for assessing bias and imprecision

7.4 Assessing bias and imprecision in product costs

Introducing measurement theory and adjusting the model to repeated measurements support the calculation of bias and imprecision. The first series of experiments focuses on illustrating bias and imprecision in a product portfolio. Table 22 describes the detailed experimental design.

Table 22: Experimental design – Bias and imprecision

Independent parameters		**Control parameters**		**Dependent parameters**
DENS	0.6	Products	50	Percentage error [PE%]
Q_VAR	1	Processes	50	Absolute percentage error [APE%]
RC_VAR	0.55	Resources	50	Bias [%]
UNIT_SHARE	0.5	Repetitions	500	Imprecision [%]
COR	0	Total costs	1,000,000€	
ERROR	[0.1,0.3,0.5]	ABC(CPH)	Correl-Size	
CP	[10,20]	ABC(CDH)	big pool	
n=150,000 products (3 · 2 · 500 · 50)				

The first set of results quantifies bias and imprecision at the product portfolio level from repeating cost measurements in a typical production environment. Selecting a typical costing scenario in the model, 10 and 20 size correlation-based cost pools using the "big pool" cost driver can repeatedly measure this environment. Once the costing system is set, the bias in the average measurand will arise from the systematic error. Additionally, imprecision marks fluctuations in different random measurement error scenarios. Hence, the product cost portfolio is shown by demonstrating the bias and imprecision in each product cost.

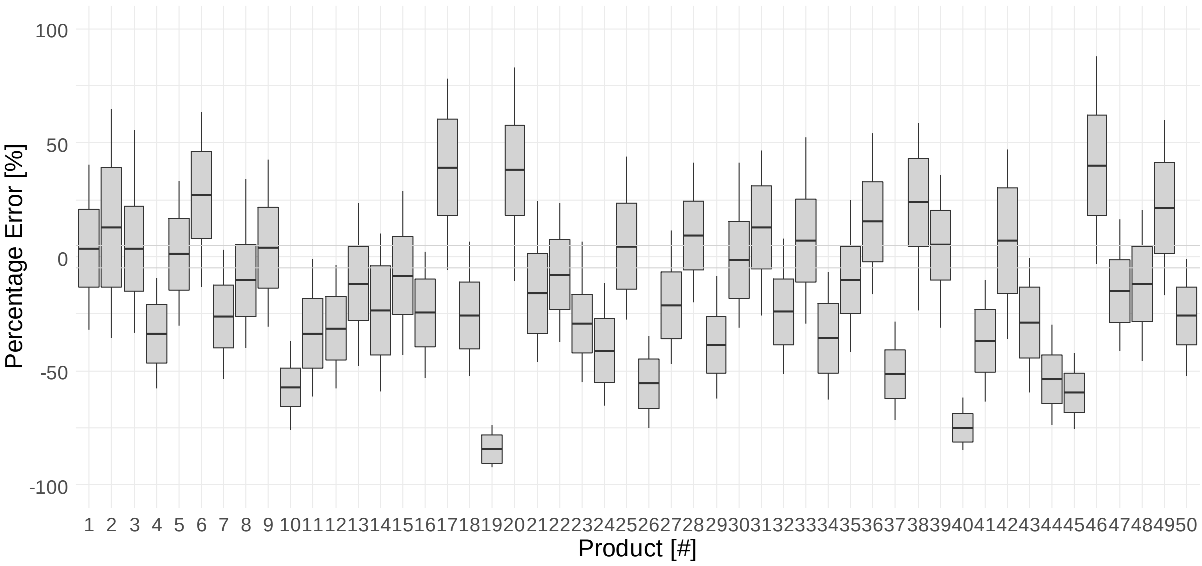


Figure 58: Bias and imprecision in a product portfolio measured using a complex costing system of 10 activity pools

Figure 58 and Figure 59 depict boxplots of the percentage errors in the 10- and 20-cost pool settings and highlight the imprecision. This number of cost pools follow the recommendation in the literature about what is considered to be acceptable (Balakrishnan et al., 2011). Interestingly, both costing systems lead to less precise product cost estimates in the same environment. Recall that random measurement errors are uncontrollable and can appear and disappear between measurements that invoke a probability of product costs.[51] This imprecision is on average 13.63% (for the 10-cost pool system) and 10.61% (for the 20-cost pool system). Notably, this is outside the accuracy range proposed by Kaplan and Atkinson (2011) in both settings, suggesting that product cost measures in ABC systems are somewhat imprecise and may be less credible.

Analyzing the results at the product level also allows me to quantify the number of products that remain within the ±5% interval on average. The grey lines in the portfolios stand for this interval delineating a ±5% error tolerance. Using this evaluation criterion, the 10-cost pool scenario shows 25% overcosted and 62% undercosted products (CP=10, the share of over- and undercosted objects is 87%). This rises to 22% overcosted and 50% undercosted products in the more disaggregated setting (CP=20, the share of over- and undercosted objects is 72%). The average bias decreases from 25.70% to 16.88%.

[51] The resulting ranage of product cost measures indicates a corresponding variation including errors that is recognizable as a degree of uncertainty (Power, 2007).

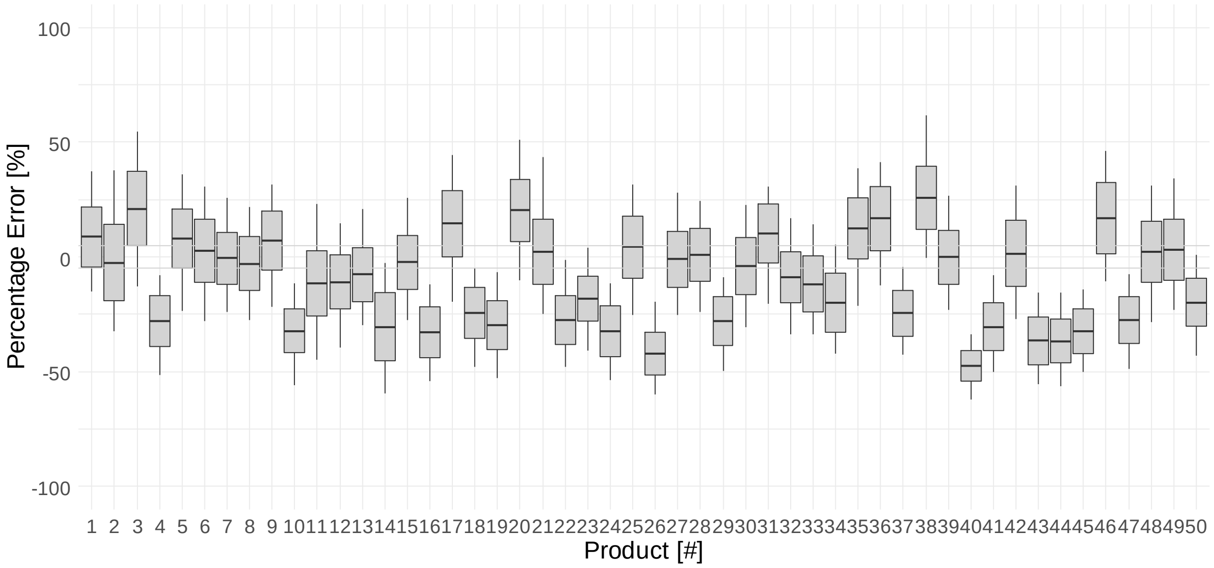


Figure 59: Bias and imprecision in a product portfolio measured using a complex costing system of 20 activity pools

Consider that cost system refinement does not always reduce the bias of product costs. Consider, for example, product #3. In the 10-cost pool scenario, it has a bias of 3.54% and an imprecision of 16.23%, while in the 20-cost pool scenario, there is a substantial increase in the bias toward 21.04% with a slightly reduced imprecision of 14.02%. For products #14, #30, and #35, the finding is the same. Hence, this thesis concludes that it is crucial to examine the individual product costs when assessing the performance of a costing system, confirming the claim by Christensen and Demski (1997).

Figure 60 shows the error variance in product costs by demonstrating the respective bias and imprecision probabilities. The density plots are continuous histograms that reflect the frequency of the appearance of data points in terms of distribution. In this case, the plots represent the spectrum of potential cost measurements for product #2, which has a bias of 12.95% and an imprecision of 26.07% in the 10-cost pool setting. Hence, measuring the “true” value is possible. However, this effect could turn from offsetting to reinforcing when a positive measurement error occurs to an error of +38.97%. To sum up, the product cost range indicates the possible space for a single measurement.

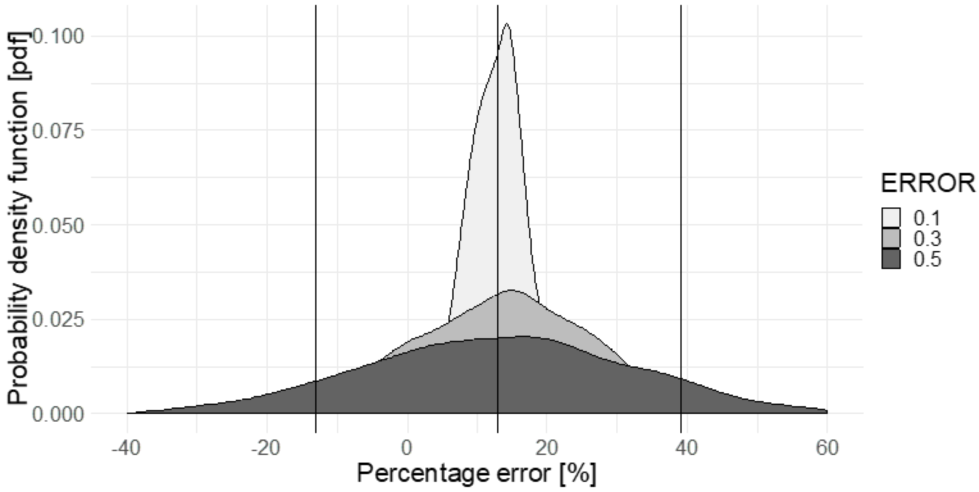


Figure 60: Product cost range among different levels of random measurement errors

In summary, the experiments demonstrate the bigger picture of errors at the product cost level by examining bias and imprecision, which are two dimensions of measurement quality with a range of product costs including non-constant uncertainty. Accordingly, single measurements may be highly inaccurate. These two factors are best taken into account to understand the bigger picture of measurement quality and the resulting information quality.

7.4.1 Persistency of bias and imprecision

The next consideration focuses on the persistence of bias and imprecision. The experimental design in Table 26 shows how the error metrics develop toward a full ABC system. All error measures decline with the increasing complexity of the costing system as expected. Of particular interest are the similarities and differences in the behavior of the error types. *APE* and absolute bias have almost the same size, with *APE* being slightly higher, as it additionally captures the effects of unsystematic errors. In addition, *APE* and absolute bias have the same slope, except for a full ABC system. Hence, this graph suggests that *APE* mainly reflects absolute bias. The slopes of absolute bias and imprecision suggest that bias is reduced much faster by refinements and, even more importantly, that a certain level of imprecision remains in the system even after full aggregation. This remaining imprecision explains why *APE* does not reach 0 toward the end.

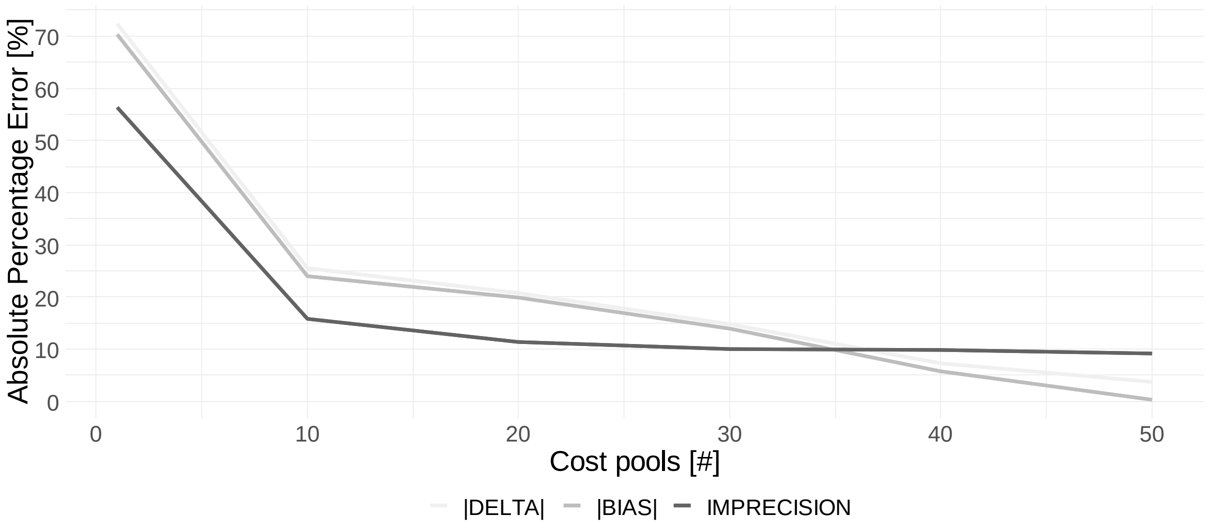


Figure 61: Full disintegration of activities in the environment. When all resource consumption is known, the costs are perfectly allocatable

Figure 61 also suggests that *APE* does not reflect imprecision sufficiently. Considering how the *APE* measure is calculated, this is only the case for product costs, where the bias is zero. With increasing bias, *APE* underrepresents imprecision more and more. As the APE and EUCD behave similarly, one can conclude that the error metrics currently used in the literature on the design of costing systems do not fully capture imprecision. Further, imprecision affects each product cost value to some extent. Although costing systems are refined, imprecision remains. By contrast, biases decrease with increasing refinements. As in other fields, this measurement imprecision could be denoted in the reported values. Hence, each product cost is affected by bias and imprecision, indicating different levels of measurement quality within a portfolio.

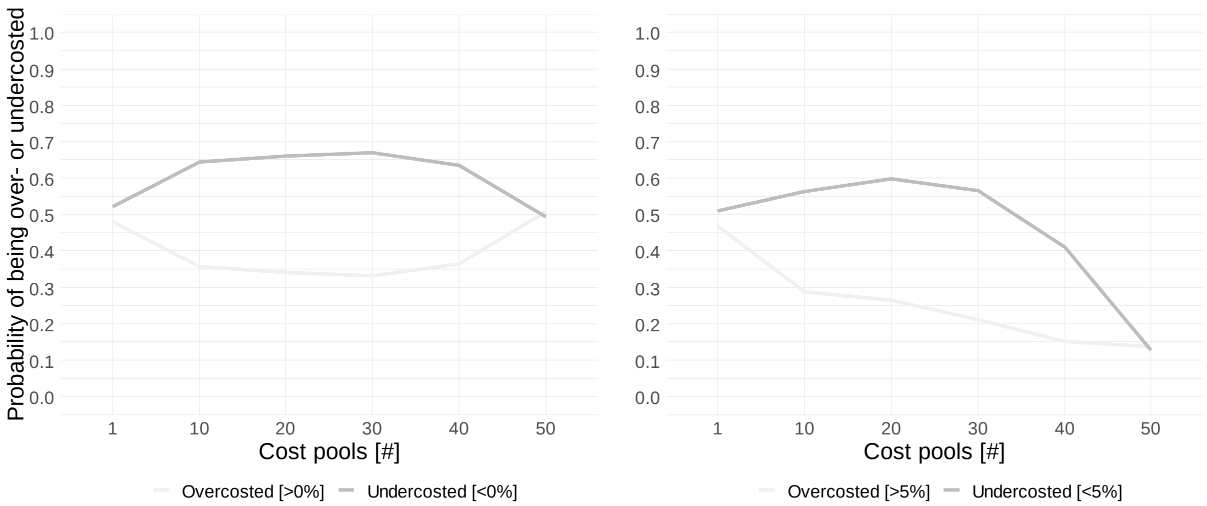


Figure 62: Average probability of a product being over- or undercosted

Figure 62 shows another observation from the data on the direction of the bias: there are more undercosted product costs than overcosted ones at the beginning. According to the data, around the beginning of more cost pools, decreasing overcosting occurs with an increasing undercosting tendency.

This confirms previous findings that undercosting is more persistent in portfolios (Gupta, 1993; Labro & Vanhoucke, 2007); however, despite more information on costing systems, undercosting rises. Indeed, it is striking that undercosting increases until the use of 30 cost pools, thereby strengthening the persistence of undercosting product portfolios.

Figure 62 highlights imprecision at 50 cost pools, meaning that a full ABC system still causes over- and undercosting. According to Horngren et al. (2014) and Drury (2015), as well as Noreen (1991), a full ABC system leads to perfect marginal product costs. However, this result demonstrates that imprecision is responsible for 14% overcosting and 13% undercosting. In sum, despite the full resolution of the production environment by cost pools, 27% have an over- or undercosted product cost. Consequently, this thesis claims that marginal costs are by no means perfect – even under a full ABC system. Finally, the exploration of the previous experiments shows for the first time that bias and imprecision matter as well as emphasizes that imprecision does not benefit from the disaggregation of more cost pools, implying that even in innovative information systems, cost accounting may be unable to approximate product costs precisely. This evidence suggests that canceling out imprecision requires the precise measurement of each allocation base.

7.4.2 Cost error behaviors in complex ABC systems

Proposing the lack of precision as an essential antecedent for cost information emphasizes the question of anticipating cost error behavior. As bias and imprecision are different error types, clear guidance could sharpen managers' perceptions. Hence, the experiment uses a large-scale dataset (n=4,860,000) to allow for the features of the production environments and costing systems to vary. Table 23 shows the experimental design, including five levels of cost pools (4, 8, 12, 16, and 20), four cost pool heuristics, and 50 products, processes, and resources. This results in a dataset of 81 economic environments under constant demand (3 levels of *RC_VAR* × 3 levels of *DENS* × 3 levels of *COR* × 3 levels of *Q_VAR*) including 50 resources and 50 products, where 540 noisy measurements were performed (1,200 = 3 levels of measurement errors × 5 levels of cost pools × 20 repeated measurements × 4 cost pool building heuristics). Most of the factors are adopted from previous research and provide a set of relevant explanatory factors.[52] Applying ordinary least squares regression with standardized coefficients, eta squared values, and F-values estimates the effects statistically.[53]

[52] We included all known "random" cost pool heuristics to allow no restrictions in cost pool building and cost driver selection choice. Cost pool heuristics can be grouped by various rules, as investigated by Balakrishnan et al. (2011). Thus, we accounted for the *random* as well as the *correlation-based* random rule that allow the "big pool" to choose different drivers even in identical environments.

[53] See Labro and Vanhoucke (2008) and Balakrishnan et al. (2011) for a similar analysis of simulation data. In addition, we follow the recommendation of Anand et al. (2019) to report effect sizes and F-values for large-scale datasets.

Table 23: Experimental design – Drivers of bias and imprecision

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,0.6,0.85]	Products	50	Absolute percentage error [APE%]
Q_VAR	[0.5,1,1.5]	Processes	50	Bias [%]
RC_VAR	[0.4,0.55,0.7]	Resources	50	Imprecision [%]
VOL_SHARE	[0.5]	Repetitions	20	
COR	[-0.6,0,0.6]	Total costs	1,000,000€	
ERROR	[0.1,0.3,0.5]	ABC(CPH)	*[1,2,3,4]*	
CP	[4,8,12,16,20]	ABC(CDH)	*Big pool*	
n= 4,860,000 ($3^5 \cdot 5 \cdot 4 \cdot 20$); CPH_1=‘random’, CPH_2 = ‘size-based’, CPH_3 = ‘correl-random’, CPH_4 = ‘size-random’				

The regressions in Table 24 show that the coefficient of determination of the bias and imprecision model is higher than that in the error model. All four models focus on different dependent variables but share the same full dataset (n=4,860,000). All the models are significant, but not all of them show the same behavior. For example, the error model and bias model share similar magnitudes and effect sizes as well as prediction powers (R^2 0.32 vs. R^2 0.34). The imprecision model has a higher R^2 (0.59) and the investigated parameters behave differently. Additionally, comparing the incidence of both coefficients indicates that product cost errors are almost entirely predictable by the model (R^2(Bias) + R^2(Imprecision) = 0.34 + 0.59 = 0.93). Hence, this thesis concludes that imprecision completes the bigger picture of errors by identifying the drivers of this kind of uncertainty.

Table 24: Regression models for identifying the drivers of bias and imprecision

	APE [%] [+]			|BIAS| [%] [+]			IMPRECISION [%] [+]		
	B	**η²**	**F**	**B**	**η²**	**F**	**B**	**η²**	**F**
Product characteristics									
PCB [%]	0.28	*0.01*	90,534	0.30	*0.02*	5,086	-0.09		12,430
INTRA [%]	0.27	*0.03*	802,272	0.27	*0.03*	42,402	0.08		9,127
INTER [%]	-0.17	*0.01*	8,104	-0.18	*0.01*	544	-0.04		13,840
COST_SHARE [%]	-0.36	*0.06*	445,869	-0.39	*0.07*	26,450	0.40	*0.11*	37,680
Cost system characteristics									
CP	-0.34	*0.14*	817,206	-0.34	*0.15*	42,271	-0.22	*0.10*	28,930
ERROR	0.03		5,176	0.00		0	0.63	*0.49*	235,100
Random [CPH_1]	-[1]			-[1]			-[1]		
Size-Correl [CPH_2]	[-1.5] [1]			[-1.5] [1]			[-0.8] [1]		
Random-Correl [CPH_3]	[-7.2] [1]	*0.01*		[-7.5] [1]	*0.01*		[-0.1] [1]		
Size-Random [CPH_4]	[-1.9] [1]			[-1.8] [1]			[-0.6] [1]		
Firm environment									
DENS	-0.05		3,143	-0.05		138	-0.12		2,087
Q_VAR	0.06		22,959	0.07		1,328	0.05		1,076
COR	0.00		135	0.00		7	0.00		7
RC_VAR	-0.05		19,695	-0.06		1,124	0.02		239
n		4,860,000			4,860,000			4,860,000	
R^2-adj		0.32			0.34			0.59	

Multicollinearity VIF Controlled < 6.5,
All models are significant ($p<0.01$),
B = Standardized Regression Coefficients, η^2 = Effect sizes F = F-value from an ANOVA model Type III;
Less intense interaction effects in terms of $\eta^2<0.01$ are excluded.
[1] Contrasts, dummy, or fixed effect variables may be misleading in their standardized beta regression coefficients due to their artificial scale. If not thoroughly acknowledged, it may cause the wrong interpretation. Hence, the regression uses unstandardized regression coefficients.

In addition, Table 24 provides evidence that regular large consumption along products' production processes drives the bias. In general, both *INTRA* and *INTER* affect bias and imprecision, with *INTRA* having a remarkable positive effect (B=0.27, η^2=0.03, F-value=41,840) and imprecision a lesser extent. Recall that *INTRA* is the heterogeneity of the technology, meaning significant consumption variance along with production processes. This results in a variety of usage and can easily distort the measurement of costs under less specific costing systems. By contrast, products with more homogeneous production are robust to costing errors (Babad & Balachandran, 1993). Thus, the data support a higher chance of product cost distortion when there is variance in higher consumption in products' production processes.

Surprisingly, *INTER* has the opposite effect for bias (B=-0.18, η^2=0.01, F-value=544). Products that differ from the average product mix or product family (i.e., large mass products compared with average products) have a lower error. Contrarily, products with less *INTER* (i.e., less demanded variants compared with average products) are more sensitive to costing errors. This result is striking because Hwang et al. (1993) demonstrate that *INTER* operates as a positive error driver in a single allocation base setting. In essence, this result suggests that *INTER* has an error-reducing effect instead of increasing with larger costing system disaggregation. Specifically, this thesis concludes that not all types of heterogeneity are indicators of potential errors when considering complex ABC systems.

Another remarkable effect occurs from the product cost structure *UNIT_SHARE*, which indicates the production output and consumption of unit-level activities. A large number of product units, on average, reduces bias but increases imprecision (Bias: B=-0.36, η^2=0.06, F-value=26,100; Imprecision: B=0.40, η^2=0.11, F-value=37,680). High volume products tend to have higher unit-level costs due to increased demand for materials, labor, and machine hours. From the data, those are seemingly better measured in contrast to others. Importantly, less bias comes with increasing imprecision. Noteworthily, the effect on imprecision is in the other direction, as it increases with higher unit-level activity in terms of cost. Striking from this evidence is that ABC systems, which are prominently suggested for measuring non-unit-level costs better, still bias these "less demanded" products downward (Cooper & Kaplan, 1992; Shank & Govindarajan, 1988). Hence, ABC systems measure products with high (low) unit-level usage with less (more) bias but probably with more (less) imprecision at the same time.

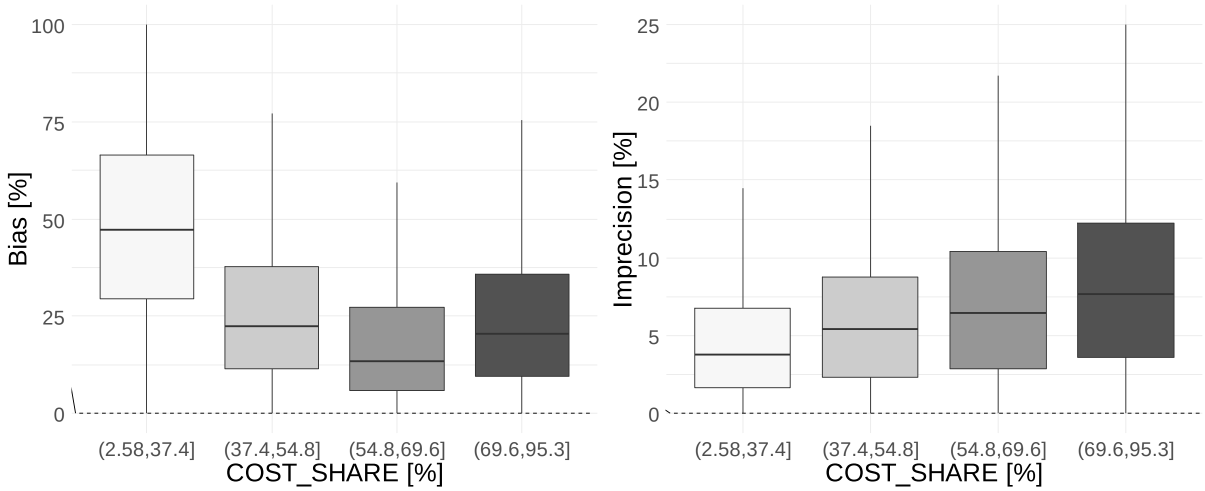


Figure 63: Left – *COST_SHARE* demonstrates classical cross-subsidization in an ABC system; Right – *COST_SHARE* demonstrates rising imprecision with higher unit-level product costs

In this direction, Figure 63 reports the data more in-depth by showing the development of bias and imprecision for *COST_SHARE*. The figure illustrates the contrary movement of bias and imprecision as the regression models indicate. Lower unit-level product costs have less bias, although the bias increases in the end again. Imprecision, by contrast, increases with unit-level costs. Therefore, this thesis concludes that mass-produced products tend to have more substantial imprecision and are more likely to be imprecise.

Further, there is still cross-subsidization in ABC systems even though they are presumed to overcome this issue. Similar to classical cross-subsidization, decreasing non-unit-level costs seem to switch the product cost error toward overcosting. This result is surprising because ABC systems should overcome classical cross-subsidization (Horngren et al., 2014; Shank & Govindarajan, 1988) by addressing more driver types (Cooper & Kaplan, 1987). This figure depicts that some cross-subsidization remains in complex costing systems, emphasizing over- and undercosting when ABC systems have not fully adapted to a production environment. Specifically, this thesis suggests the rule of thumb that cross-subsidization remains even in sophisticated costing systems, although to a lesser extent for high and low volume products.

As expected, an increasing number of cost pools *CP* leads to a reduction in bias, but it also substantially reduces imprecision (Bias: B=-0.34, η^2=0.15, F-value=42,271, Imprecision: B=-0.22 η^2=0.10, F-value=28,930). Intuition suggests that more cost pools, meaning higher sophistication, should reduce all kinds of errors, which the model confirms in that having more cost pools reduces bias and imprecision. To rule out that the findings depend on a specific cost design, the experiment included several cost pool-building heuristics to increase the robustness of the analysis to different cost designs. The heuristics are measured using fixed effects in the dataset, where the basis is the random grouping. As expected, there is a reduction in bias and imprecision in terms of correlation-based cost pools.

By contrast, the "correl-random" allocation of resources to cost pools is less sensitive to bias (Bias: b=-7.5, η^2=0.01). Intuitively, error reduction comes with more homogeneous cost pools, as shown by, among others, Balakrishnan et al. (2011). For imprecision, by contrast, costing systems may have less influence. This thesis infers that a cost system designer has no lever in cost system design choice to handle and reduce imprecision. The production environment characteristics offer little information, probably because the product-level category fits better. Hence, all the environmental parameters such as *DENS*, *Q_VAR*, *UNIT_SHARE*, *COR*, and *RC_VAR* have less effect on bias and imprecision.

Summing up, the regression analyses support the bigger picture of errors. In particular, the models using bias and imprecision as a dependent variable have much higher explanatory power than the models using a "summed total error". In addition, looking at the products leads to several useful patterns describing error behavior in the portfolios and helps identify the antecedents of cost systems with low bias and high precision. Still, the analysis also uncovered some trade-offs to be considered when designing cost systems.

Concerning the drivers of bias and imprecision, the regression analyses support the higher prediction capabilities of separate bias and imprecision models compared with the previously used error metric. This supports the claim that both measurement characteristics matter and follow partly different logics. Further, ABC systems measure products with high unit-level costs with less bias but with more imprecision and vice versa. In other words, there is the potential trade-off that mass-produced products are more robust to biases but more sensitive to imprecision. Importantly, products with high non-unit-level costs are still biased downward on average despite the proposition that ABC systems should measure simple and complex objects more. Thus, an ABC system is more efficient when measuring the resource consumption of simple products but does not strictly improve complex ones in contrast to existing guidance.

7.5 Cost-based decision-making

7.5.1 Decision-influencing: Product cost evaluation

The previous section provided robust evidence that product costs can have bias and imprecision depending on specific antecedents. Acknowledging bias and, in particular, imprecision provides the bigger picture for anticipating the quality of (cost) accounting information. Nonetheless, imprecision has not yet been considered intensively in this context, even though many analytical studies have incorporated error variance in their models (e.g. Banker & Hughes, 1994; Hölmstrom, 1979, 1982). In particular, it is regularly assumed to be independent and constant (Antle & Demski, 1988; Feltham & Xie, 1994), which does not match the results of this thesis. The presented results highlight a different picture because product cost imprecision is neither equally distributed across products nor equally under demand changes. In this line, this subsection aims to construct scenarios to address the implications of imprecision on further cost-based decision-making.

Research has considered this to be a crucial element in (performance) evaluation (Banker & Datar, 1989; Christensen, 2010; Feltham & Xie, 1994; Hölmstrom, 1979). Banker and Datar (1989) stress that a lack of precision reduces signal intensity, meaning that information is inconsistent. Therefore, imprecision dilutes signals because the congruity between action and measure is less observable. As a result, an imprecise signal is not optimal for measuring an agent's actions, which outweighs the importance of an aggregated measure and raises the cost premium for motivating the agent. Feltham and Xie (1994) argue that imprecision makes incentivizing more costly because it increases agents' risk (i.e., they are less responsive to incentives). Overall, the discussion on imprecision is conflicting; however, most studies have followed an independent variance assumption. Again, the last section provides evidence that a constant independent assumption of error variances does not hold for cost accounting.

To investigate the implication of biased and imprecise cost information, an analysis of managers' perceptions in performance evaluation through Bayesian updating may be promising (Christensen, 2010; Lewis, Shields, & Young, 1983; Moore & Healy, 2008; Stein, Beer, & Kreinovich, 2013). Bayesian updating has occasionally missed representing the right personal belief (Hogarth & Einhorn, 1992); however, it remains an often used belief framework in research, particularly in economics (Gigerenzer & Hoffrage, 1995; Slovic & Lichtenstein, 1971; Van den Steen, 2011; Zellner, 2002), for testing the implications of inconsistent data on forming and updating a belief. It thus provides a suitable method for examining managers' perceptions and belief updating from biased and imprecise product cost information.

Bayesian updating generally models a belief-building process from a sequential information perception. Imagine a person with a prior intuition who receives new information continuously that either confirms or rejects his or her intuition. This setting underlies the Bayes' theorem shown in equation (21). No matter whether supporting or rejecting information, the prior belief will be updated with new data, yielding a posteriori belief. Concerning equation (21), the prior belief is the probability P(A), where the new information B contains a normalization P(B). Then, the new information P(B) supports the prior belief with a certain likelihood P(B|A). Altogether, this yields the weighted posterior belief P(A|B).[54]

$$P(A|B) = \frac{P(B|A)}{P(B)} P(A) \tag{21}$$

Figure 64: A Bayesian updating model of a principal when receiving new information

illustrates a Bayesian-rational agent (Van den Steen, 2011) who sequentially updates his or her belief using new data in the experiment. The experiment can be a monitoring process of several product cost reports from an information system (John, 2016). This likely results in a modern performance evaluation context that can be applied at many hierarchical levels. Another possibility is that managers control their agents by observing their actions through product cost data. Irrespective of which setting is applied, a person builds his or her belief about a performance measure such as product costs. To ensure consistency, controlling the product cost is rather straightforward; however, in the experiment, managers receive inconsistent product cost information that is biased and imprecise.

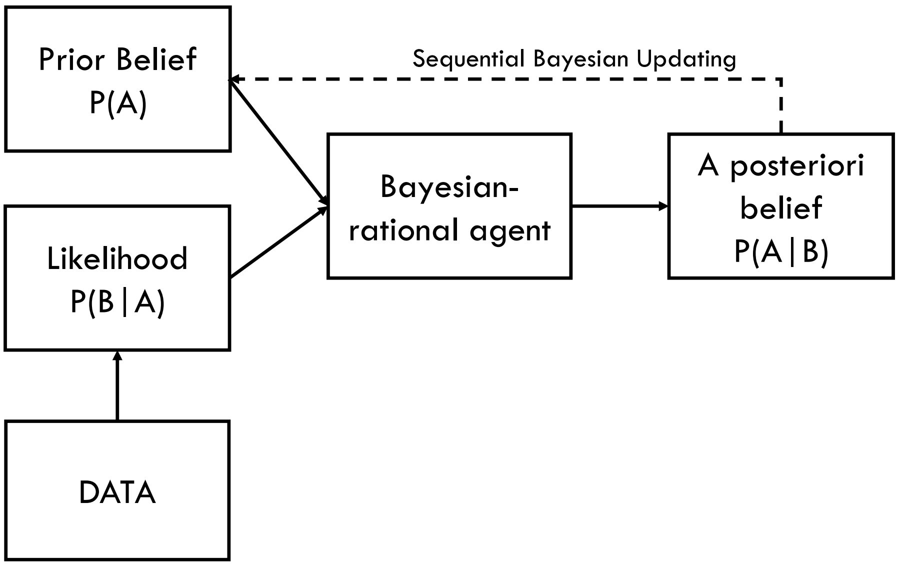


Figure 64: A Bayesian updating model of a principal when receiving new information

Before proceeding, a numerical example of one Bayesian update in the context of controlling the product cost is given. Imagine costs for one product of 50€ in the period T_0. Importantly, a period has no defined timeframe, but at T_1, costs increase to 100€. Of course, the difference is 50€ when there is zero imprecision, underlying the informativeness principle. However, Bayesian interpretations can

[54] The calculation of Bayesian updating was performed in closed form, as described in the appendix.

compensate for inconsistency and the lack of credibility. Therefore, there is imprecision at T_0 of σ_0=5€ and σ_1=10€ at T_1. This scenario has inconsistent information through simple autocorrelated error variance in terms of imprecision (Christensen, 2010). Assuming the person knows about the informativeness, the posterior belief is 66.66€ instead of 100€ because the new information at T_1 is less credible and informative and, thus, it influences updating in the direction of the informative prior belief. When both estimates are equally informative, meaning there is no difference in imprecision (σ_0=σ_1=5€), the updated belief is 75€. Finally, imprecision reduces the informativeness, as accounting studies suggest (Amershi et al., 1990; Amershi, Demski, & Fellingham, 1985; Banker & Datar, 1989), making the final belief less predictable.[55]

Figure 65 illustrates the events of the recursive Bayesian updating used for the experiment. Assuming T_0 as the starting point, the prior belief may be a cost target, expectation, intuition, or merely the last cost report. New information arises from the costing system and updates the prior belief to the posterior belief. In the next round, the posterior belief is the new prior belief of T_1. The updating will repeat until it is stopped.

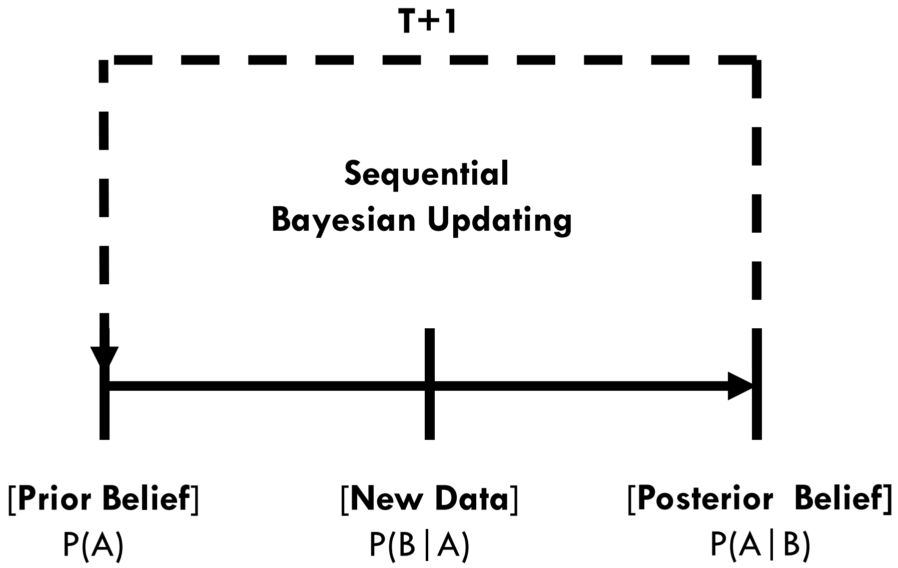


Figure 65: Belief updating using recursive Bayesian updating

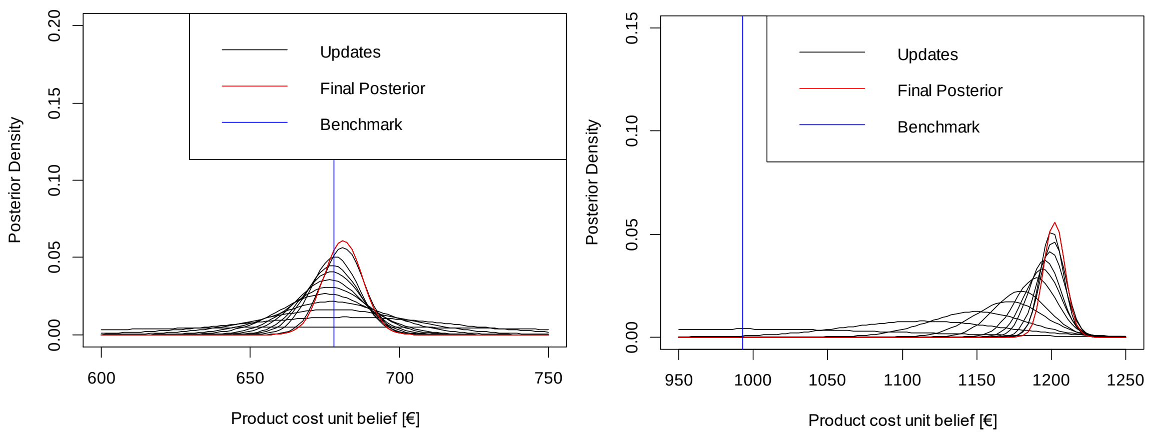
Bringing all the parts together, the experiment has two sub-experiments: the first analyzes the perception under bias and imprecision among fixed product costs and the second examines how managers perceive product cost increases and decreases. At the beginning of each experiment, the Bayesian-rational agent will have a prior belief of the "true" product costs, including an imprecision from the corresponding product cost estimate. Next, the costing system will provide new product cost

[55] The calculation of Bayesian updating is challenging, especially when lacking conjugate priors. Hence, it is important that the data have an identical underlying distribution. When this is not the case, rather complicated approximation procedures are needed to solve the updating. Fortunately, product costs' imprecision tends to be normally distributed, and this thesis generally supposes normality for all product costs and their imprecision.

data, which will enforce belief updating. Whether costs are increasing, decreasing, or constant, the new cost data are biased and imprecise. As a result, the belief will deviate from the benchmark.

Figure 66 demonstrates the first experiment of updating one product; Panel A illustrates a set of only imprecise product cost information and Panel B a scenario of biased and imprecise information. The experiment performs 12 updates for learning and processing. In Panel A, product cost information is 678±155€; however, managers do not know about imprecision, as in the real world. Therefore, the updates strengthen the believed credibility more even though real imprecision does not vary. After the updates, managers' belief converges to 681±13€, which actually "overprecises" the "true" product cost information. In the same experiment with biased and imprecise cost information, managers' belief nears the biased information as expected, which shows the impact of bias in perception. More interestingly, overprecision rises from 1219±226€ to 1201±14€. Both results indicate that managers' belief in the product cost information will increase despite imprecision. This thesis thus claims that imprecise product cost information can lead to overconfidence in cost accounting data (Moore & Healy, 2008; Van den Steen, 2011).

Panel A: Belief updating under imprecision Panel B: Belief updating under bias and imprecision



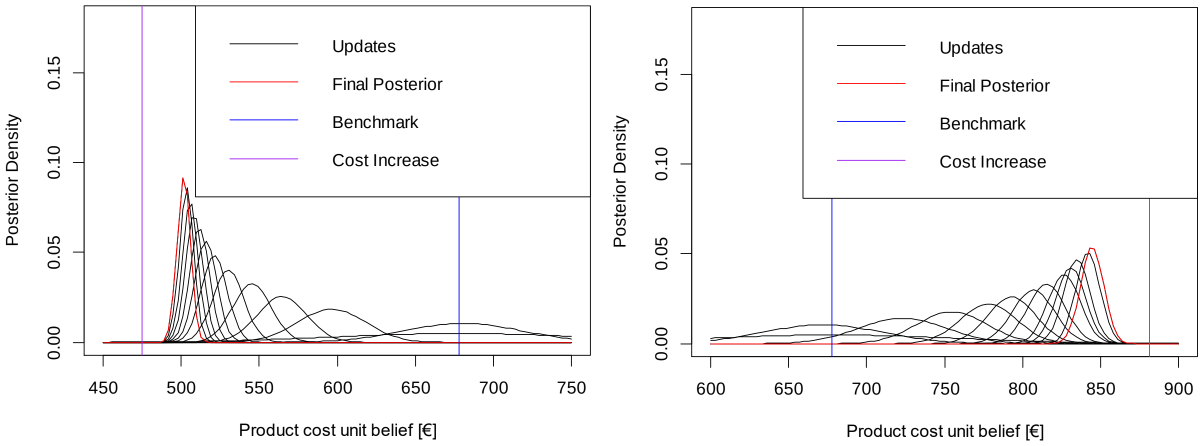
	Cost information				Managers' belief
	PC_0	PC_1	Bias	Imprecision	Final Belief
Panel A	678€	678€	0	±155€ [22.40%]	681±13.08€ [0.44±1.92%]
Panel B	993€	1219€	+226€ [24.22%]	±184€ [18.59%]	1201±14.30€ [20.95±1.44%]

Figure 66: Panel A (left) demonstrates how a manager perceives cost information under imprecision. Panel B (right) shows the perception under bias and imprecision.

The second experiment considers a product cost increase with hidden product waste and a product cost decrease with unobserved efficiency. Again, the manager starts with a prior product cost belief; then, in the next period, an increase (30%) or decrease (30%) occurs. The manager does not know what happens but can anticipate the action from the product costs. In this regard, the product costs are performance measures.

Figure 67 demonstrates that the product cost increase is less perceptible than the product cost decrease. Panel A shows the increase of PC from 678€ at T_0 to 881€ at T_1. There, the final cost belief is 844±7.30€, which covers 24.48% of the "true" 30% increase. Panel B shows a decrease from 678€ (T_0)

to 475€ (T_1), where the belief ends up being 501±4.27€. There, managers believe there is a reduction of 26% instead of 30%, which highlights the difference between belief updating. Thus, this thesis concludes from this experiment that imprecision dilutes product cost changes and that increases may be less credible than decreases.



Cost information			**Managers' belief**
PANEL A: Product cost increase of 30% by an action			
	PC	Imprecision	Final belief
T	678€	±155€ [22.40%]	
T_1	881€	±184€ [18.59%]	844±7.30€ [Cost increase of 24.48%]
Δ(Cost)	+203€ [+30%]	±29€ [4%]	
PANEL B: Product cost decrease of 30% by an action			
	PC	Imprecision	Final belief
T_0	678€	±155€ [22.40%]	
T_1	475€	±88€ [11.80%]	501±4.27€ [Cost decrease of 26.00%]
Δ(Cost)	-203€ [-30%]	±67€ [11%]	

Figure 67: Panel A (left) shows a product cost increase. Panel B (right) shows a product cost decrease.

Summarized, the lack of precision affects signals' informativeness (Amershi et al., 1990; Banker & Datar, 1989; Hölmstrom, 1979), which is decisive for the decision-influencing role of costs in costing systems. The previous experiments have shown that imprecise product cost information weakens signals' intensity and mitigates the correct perception of hidden actions (i.e., product waste). This comes as a surprise because error variances are prominently presumed to be constant and independent. Another related finding concerns knowledge about imprecision. In particular, when managers are not careful about imprecision, they are likely to "overprecise" cost information, which is a quantification of overconfidence bias.

7.5.2 Decision-facilitating: Pricing

This subsection shows how imprecision impacts cost-based pricing (Balachandran et al., 1997; Balakrishnan & Sivaramakrishnan, 2002) in terms of profit. In particular, I refer to the optimal pricing decisions in the work of Banker and Hughes (1994), who analytically develop an optimal pricing decision mechanism that can overcome decentralized information dissemination while using product costs. Hence, product costs are relevant for pricing, which influences demand in turn. Lastly, demand leads to corresponding production capacity commitments.

However, the optimal decision relies on consistent product cost information, with a recent discussion about pricing decisions when product costs are distorted. Homburg et al. (2017) incorporate the impact of pricing and capacity decisions from noisy product costs in a single setting. Anand et al. (2017) consider elimination decisions in a dynamic setting but exclude demand functions. This thesis covers both studies and adopts a dynamic setting focused on pricing decisions because cost-based pricing still plays an enormous role in profitability (Banker et al., 2002; Banker & Potter, 1993).

In accordance with Banker and Hughes (1994) and Banker et al. (2002), optimal pricing requires α (maximum demand of a product), β (price sensitivity), and marginal product unit costs PCb. When products are correctly measured, this results in the optimal price $\widehat{\rho^*}$ assuming a monopoly. Taking this into account, equation (22) results in an optimal pricing decision.

$$\widehat{\rho^*} = \frac{\alpha}{2\beta} + \frac{PCb}{2} \tag{22}$$

The market reacts with expected demand $\bar{q}$ on the price commitment in accordance with equation (23). Equation (23) is a simple linear demand function accounting for maximum demand α and price sensitivity β.

$$\bar{q} = \alpha - \beta\widehat{\rho^*} \tag{23}$$

However, both equations have consistent information, and thus the experiment focuses on biased and imprecise cost information. For analytical simplicity, it also assumes that expected demand is equal to realized demand ($\bar{q} = q$) and that selling products increases firms' profit $(\widehat{\rho^*} - PCb)q$. In addition, the experiment adopts the full utilization setting, thereby assuming fully variable product costs to decompose the optimal capacity decision. Overall, both increases and decreases in the profit function in equation (24) lead to worse pricing decisions and thus incorrect cost information.

$$E(\pi) = (\widehat{\rho^*} - PCb)q \tag{24}$$

Demonstrating the profit implications of cost errors, the model runs this as the benchmark for optimal pricing PCb. Less optimal pricing first affects the market and then potential profit. When product prices are overexaggerated, demand decreases to zero. Then, the firm eliminates this product as in Anand et al. (2017). Hence, implementing inconsistent cost information, this thesis uses the same equations but chooses PCh.

Figure 68 shows the dynamic progress of the experiments, starting from a specific production environment setting that continuously prices and sells products for 100 periods. While this is a dynamic model, every period receives an input from the previous output, as indicated by the dashed line. At the beginning, product costs are used to set prices, which then determine the contribution margin and demand. Consequently, customers purchase the products demanded, which determines the resource consumption in the next period.

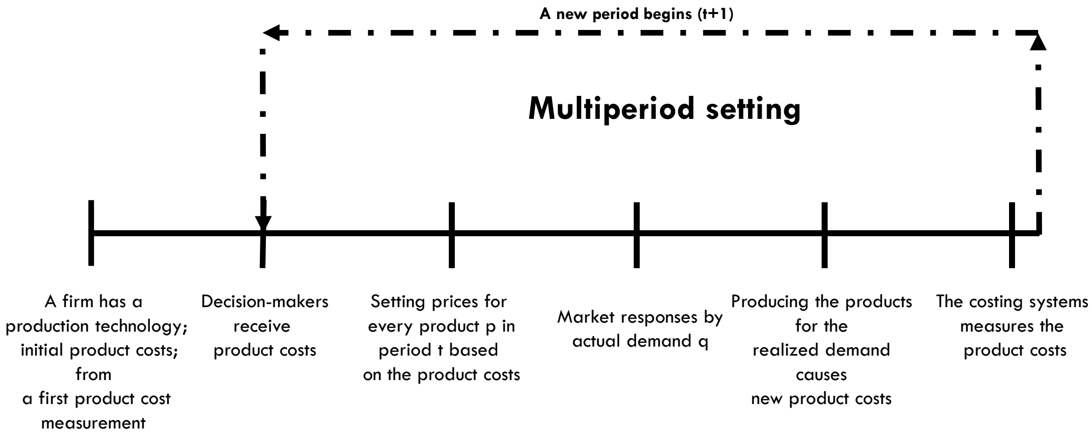


Figure 68: Event line of the pricing experiment

Intuitively, customers' and competitors' price sensitivity decides the impact of cost-based pricing. Before digging deep, explaining the demand parameters α and β is necessary to understand sensitivity to pricing errors. When demand α and inelastic pricing behavior β are sufficient, the environment is less sensitive to errors and fewer negative consequences may emerge from false pricing (i.e., β= [5,7.5,10]). By contrast, when there is price sensitivity (i.e., β= [12.5,15,17.5,20]), the penalties for wrong product pricing decisions reduce profit. To address this issue, this thesis first performs a sensitivity analysis of β.

The first experiment deals solely with imprecision in product costs and tests different levels of price sensitivity on profit β=[5,7.5,10,12.5,15,17.5,20]. Figure 69 illustrates the impact on profit from this dynamic setting. This experiment first finds that imprecision affects firms' profit in a decision-facilitating role. From this observation, this thesis concludes that the price sensitivity β of products is indeed remarkable for the economic impact of erroneous pricing.

Another theme identified in the simulation responses in Figure 69 is the steady decline in profit under imprecision. Specifically, levels 15, 17.5, and 20 of β show how profit can reduce over time. Similarly, there is a rapid drop at the beginning of the periods that afterward continue with a creeping profit loss. Hence, this thesis infers that imprecision has a continuing negative impact on profit.

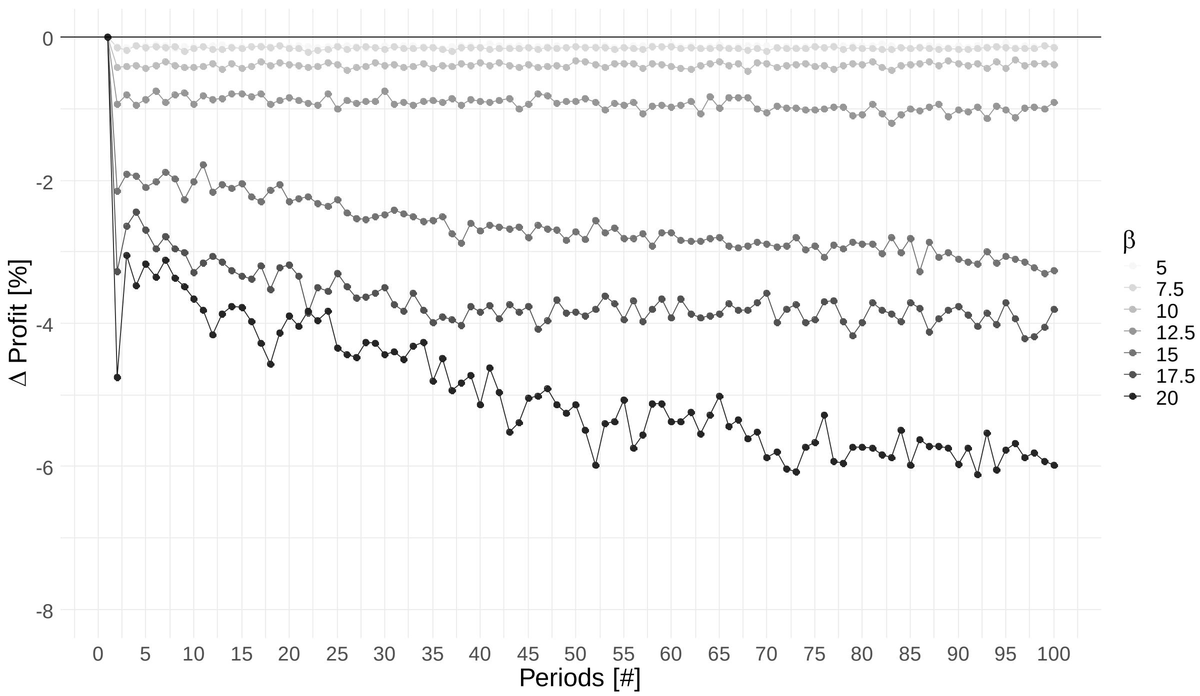


Figure 69: Evaluating pricing along with different price sensitivities

Figure 70 demonstrates four panels that contain a 2x2 design accounting for all the combinations with bias and imprecision. Panel A has no errors at all, whereas Panel B shows the impact of bias in a complex ABC system with 10 activity cost pools. The bias is constant, where overcosted products sooner or later disappear because they will lose market share. Nevertheless, after a transient oscillation, the portfolio adopts a steady state. Panel C shows the impact of imprecision on profit. While there are fewer profit losses, imprecision does not end up in the equilibrium as in the bias experiment. Most striking is Panel D, which reports the interaction between bias and imprecision. Interestingly, there is less fluctuation than in Panel B and more substantial losses than in Panel C. In the end, the firm's profit has halved compared with the benchmark scenario.

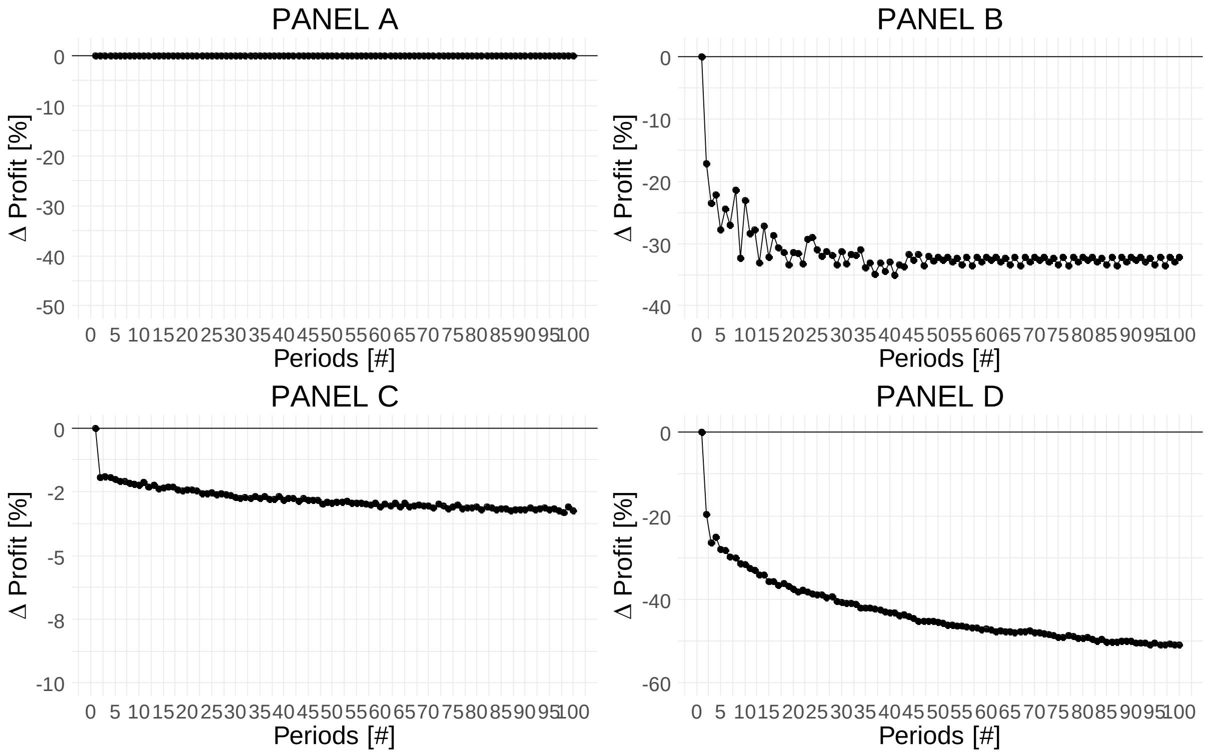


Figure 70: Profit loss effect of erroneous cost information: Panel A: Benchmark; Panel B: Bias; Panel C: Imprecision; Panel D: Bias and Imprecision

Overall, bias and imprecision have economic consequences on firms from small to large losses. Whereas the outcome of biased product cost information was rather expected, the implication from imprecision was not. This experiment highlights the different qualitative behavior of imprecise and biased product cost information. Therefore, both are relevant to consider in product cost decisions. Notably, price-sensitive products forfeit market share when imprecision holds. Having bias and imprecision, an interacting effect rises and enforces a creeping profit loss.

7.6 Contribution

Product cost measurement and the resulting cost information is of interest both in academia and in practice (Krishnan, 2015). The presented numerical experiments assessed the accuracy of product costs with respect to bias and imprecision by applying general measurement theory. These experiments are therefore among the first to use this theory to evaluate information quality dimensions. Therefore, this thesis departs from previous studies and makes the following unique contributions.

Bigger picture on errors through measurement theory

This thesis contributes to the error modeling of accounting information by capturing inaccuracy via the two quality dimensions of bias and imprecision. Measurement theory can simply differentiate systematic and random errors, where the latter are less considered in accounting settings, because the existing assumption about imprecision is constancy and independence. In addition, previous cost accounting research has used single measurements, which cannot account for the dispersion of random measurement errors as imprecision (Babad & Balachandran, 1993; Balakrishnan et al., 2011; Homburg, 2001; Hwang et al., 1993; Labro & Vanhoucke, 2007, 2008). Therefore, the repeated measurement of the numerical exploration has provided a new insight that product cost errors consists of bias and imprecision.

Cost (error) behaviors

Next, this thesis extends cost accounting knowledge in terms of cost error behavior that guide typical error patterns in product costs in complex ABC systems. The bigger picture on the errors in bias and imprecision unveils the following error behaviors: ABC systems still measure product costs with large transactional activity usage with an undercosting bias, whereas objects with more unit-level activities are somewhat accurate. The standard literature hypothesizes that the ABC system may be more effective at measuring complex products (Cooper & Kaplan, 1987, 1988). In addition, heterogeneity loses its distorting effects in multiple cost pool settings in contrast to the previously investigated single cost pool setting (Horngren et al., 2014; Hwang et al., 1993). Another remarkable error behavior is that high volume products are less biased, whereas low volume ones still struggled with undercosting in ABC systems. Therefore, mass or standardized products are less biased, whereas services or more complex products with substantial non-unit-level costs are still strongly undercosted. Overall, cross-subsidization is still observable in complex ABC systems, although the literature advocates them as a remedy in this respect (Cooper & Kaplan, 1987, 1991; Horngren et al., 2014).

Information quality through measurement quality

This thesis also contributes to the discussion on information quality and increasing data in management accounting. Measurement is a cornerstone in accounting, with information technology likely to help data collection. This thesis analyzed a full ABC system that can reduce bias to zero. However, this does not entirely prevent the error because imprecision persists. Therefore, more complex costing systems will not necessarily eliminate imprecision (Krishnan, 2015; Quattrone, 2016). Hence, this thesis claims that having *more data does not strictly lead to better outcomes* when making decisions using cost accounting data.

Decision-making

When not fully preventing imprecision, this thesis also shows that inconsistent cost information affects cost-based decision-making. There is a compelling discussion about inconsistent cost information (Anand et al., 2017; Homburg et al., 2017) that emphasizes the implication of false cost information. This thesis offered evidence about how imprecision affects the decision-influencing and decision-facilitating role of product costs. The reported findings have serious implications for managers' decision-making and stress the requests of accounting information by the IASB (2018).

The first experiment provided evidence that cost changes under imprecision are less perceivable. This parallels the previous analytical work of Hölmstrom (1979) and Banker and Datar (1989) because less informativeness weakens signals' intensity. As a result, principal-agent settings as well as performance evaluation are not optimal because of the lack of precision. Moreover, this thesis claims that unknown imprecision fosters overconfidence effects (Moore & Healy, 2008; Van den Steen, 2011). Concerning the role of decision-facilitating, imprecision has a creeping profit-reducing effect under continuous cost-based pricing. Further, biases distort optimal pricing. However, this thesis introduced imprecision as decisive, too, where the combination of bias and imprecision seemingly leads to profit losses.

8. Overall conclusion

This thesis started with the general question of measuring and managing product costs “right”, which is challenging, at least partially, because of their unobservable and interdisciplinary nature. While product costs are still not fully observable for measurement, cost management interlinks with engineering and general management fields, resulting in a dispersed field. Further, although unobservability limits empirical investigation (Balakrishnan et al., 2012a), multi- and interdisciplinarity prevent knowledge diffusion (Raasch et al., 2013) and fail to provide a common theoretical foundation.

Offering greater insight into both these fields, this thesis developed the EAD as a theory-orientated framework consisting of engineering design and economic theory to examine product-based planning in a decision context. This framework was used to test the existing guidance on modularization in terms of its cost-saving potential. The subsequent numerical exploration formalized and identified a non-linear cost-saving effect of the product architecture. Moreover, this thesis extended research on the horserace between simple and complex product costing. The evidence suggests that the superiority of complex ABC systems is sensitive to firms’ cost structure and that direct costs do not necessarily favor a specific costing system. In the end, this thesis discussed the lack of precision in product cost information that adversely affects optimal decision-making. In the worst cases, it may yield overconfidence and profit losses.

As well as other studies, this thesis is subject to limitations. One major concern is less an empirical validation and more a general issue in M&S (Rand & Rust, 2011; Smith & Rand, 2018). There is indeed less convincing evidence that the modeled benchmarks fully overlap with realistic product programs and their production technology. Imagining what is necessary to move reference firms closer to reality by still supplying generalizable and reproducible findings is ambitious. First, one has to collect a large sample of “true” product programs and their respective production technologies. For instance, this requires the identification of customers’ needs and full traceability of costs. This is problematic because marketing struggles to provide such information and cost data are sensitive for firms, causing diligence and confidentiality issues. In addition, data collection implies large, costly, and time-consuming efforts to raise data quality. From this perspective, one could encourage M&S despite less empirical validation. Specifically, while this thesis sought further empirical validation, other communities are already down this road. These works thoroughly combine computational results with empirical observations, with the management and engineering communities at the forefront. Nevertheless, this thesis draws contributions from a rich pool of results, with the following remarkable in a general context.

[1] First, this thesis proposes a theory-connecting framework that bridges engineering design and economic firm theories. This framework addresses questions from both fields in product-based planning processes. It also offers a solid theoretical foundation for design modeling (i.e., fundament for computational studies), which may pave the way for more investigations. Importantly, it outweighs earlier limitations of the AD by extending it to a new multiproduct perspective. This is particularly valuable because single performance product evaluation may oversee the product family picture. Additionally, the framework combines the understanding and concepts of both communities that frequently criticize and analyze common problems from different angles (Anand et al., 2019; Anderson & Dekker, 2009a; Campagnolo & Camuffo, 2010; Davila & Wouters, 2006; Fixson, 2007; Hazelrigg, 1998; MacDuffie, 2013). The blockage likely leads to the issues of disintegrated knowledge and slower theory development (Birnbaum, 1981; Raasch et al., 2013; Tranfield et al., 2003), where the EAD builds the necessary bridges through its integrated formalism and model-based character. This formalized skeleton for questions and profit-orientated decision-making in product-based planning supports further exploitation through computational and empirical models, which may be the starting point for new research projects.

[2] This thesis adds to the discussion on cost-saving effects in modularization by disentangling the mechanisms of vertical and horizontal leveraging from the product architecture. The product architecture is among the most crucial concepts for designing potential cost-saving effects when applying modularization (Fixson, 2005, 2006; Mikkola, 2007; Mikkola & Gassmann, 2003). Using the EAD as a framework allows investigation into formalized processes of modularization throughout product programs. When testing recommended strategies for vertical and horizontal leveraging (Meyer & Lehnerd, 1997; Moon & Simpson, 2014; Otto et al., 2016) and further differentiating them, this thesis finds compelling evidence. Arguing that vertical leveraging differs from vertical scaling, overdesigned modules provide cost savings in more stringent conditions. This thesis finds that expected and realized demand as well as the integrality of the product architecture are crucial for cost efficacy in this design mechanism. Horizontal leveraging, advocating at swappable modularity (Otto et al., 2016), displays an unexpected non-linear cost effect along the contingency of integral and modular product architectures. This general finding suggests that the largest cost-saving potential is from integral product architectures, while low to moderate integrality raises the chance of cost increases. Specifically, components with large function sharing are most doubtful for cost savings, which prioritizes the degree of component function sharing when constructing modules. Overall, this thesis modeled modularization in a reproducible and theory-orientated framework that provides a potential future path for intense discussions and theory development.

[3] Next, this thesis contributes to the choice of cost system designs while further disentangling the antecedents of the accuracy of complex and simple costing systems. Simple TVC systems should use aggregated allocation bases, although recommendations differ. Further, classical cross-subsidization does not fully follow the production output concerning over- and undercosting, where, especially, overcosting is subtler. Simple, high volume products have rather accurate product costs (Horngren et al., 2014). This thesis thus questions the applicability and necessity of the ABC hierarchy because a traditional view with variable and fixed costs behaves identically from a qualitative viewpoint. In the same vein, a TVC system does not suffer from accuracy for high batch-level costs. This additionally questions the cost hierarchy. Consequently, an indication of complex ABC systems mainly corresponds to product-level costs or a share of fixed costs. Additionally, this thesis demonstrates that despite increasing information technology and the larger potential of direct costs, cost allocation remains relevant. Overall, this study has gone some way toward enhancing cost system design choices, showing when complex ABC systems actually pay off and the efficient cost drivers in simple systems.

[4] Finally, this thesis emphasizes bias and imprecision as necessary error types for obtaining the bigger picture. Measurement theory uses bias and imprecision to recognize uncertainty in measurands, and accounting information systems are no exception. Therefore, it may be worthwhile to see accuracy as a bigger picture of errors, with cost information only accurate when it is unbiased and precise (Mertens & Meyer, 2018). Considering the lack of precision is not new in management accounting (Banker & Datar, 1989; Datar et al., 2001; Feltham & Xie, 1994; Krishnan, Luft, & Shields, 2005), but it has been neglected in the context of product costing. This thesis finds that assumptions of independence and constant variance do not necessarily hold because imprecision varies in strength and direction for every product regarding its specific antecedents. In addition, observations show that high levels of imprecision persist in complex ABC systems despite substantial refinements to cost pools. Thus, although the ongoing development of information technology improves measurements, it does not necessarily strengthen the quality of outcomes. Concerning cost-based decision-making, imprecision is qualitatively different from bias because a lack of precision affects performance evaluation through less perceivable cost increases. When not recognizing or teaching managers about this imprecision, the phenomenon of overconfidence may appear (Moore & Healy, 2008; Van den Steen, 2011). Further, this thesis shows that pricing also causes profit losses, especially when appearing with bias. Overall, this thesis thus claims that it is dangerous to neglect imprecision as an error type if wishing to avoid negative economic consequences.

9. References

Abbott, B. P., & et al., m. a. (2016). Observation of Gravitational Waves from a Binary Black Hole Merger. *Physical Review Letters, 116*(6), 061102. doi:10.1103/PhysRevLett.116.061102

Abdelkafi, N. (2008). *Variety-Induced Complexity in Mass Customization - Concepts and Management*. Germany, Berlin: Erich Schmidt Verlag.

Abernethy, M. A., Lillis, A. M., Brownel, P., & Carter, P. (2001). Product diversity and costing system design choice: field study evidence. *Management Accounting Research, 12*(3), 261-279. doi:10.1006/mare.2001.0168

Adams, K. M., Hester, P. T., Bradley, J. M., Meyers, T. J., & Keating, C. B. (2014). Systems Theory as the Foundation for Understanding Systems. *Systems Engineering, 17*(1), 112-123. doi:10.1002/sys.21255

Akao, Y. (1990). *Quality function deployment: integrating customer requirements into product design*. USA, MA, Cambridge: Productivity Press.

Al-Omiri, M., & Drury, C. (2007). A survey of factors influencing the choice of product costing systems in UK organizations. *Management Accounting Research, 18*(4), 399-424. doi:10.1016/j.mar.2007.02.002

Albach, H. (1980). Average and Best-Practice Production-Functions in German Industry. *Journal of Industrial Economics, 29*(1), 55-70. doi:10.2307/2097880

AlGeddawy, T., & ElMaraghy, H. (2013). Optimum granularity level of modular product design architecture. *CIRP Annals, 62*(1), 151-154. doi:10.1016/j.cirp.2013.03.118

Amershi, A. H., Banker, R. D., & Datar, S. M. (1990). Economic sufficiency and statistical sufficiency in the aggregation of accounting signals. *The Accounting Review, 65*(1), 113-130.

Amershi, A. H., Demski, J. S., & Fellingham, J. (1985). Sequential Bayesian Analysis in accounting settings. *Contemporary Accounting Research, 1*(2), 176-192. doi:10.1111/j.1911-3846.1985.tb00375.x

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling, 229*, 25-36. doi:10.1016/j.ecolmodel.2011.07.010

Anand, V., Balakrishnan, R., & Labro, E. (2017). Obtaining Informationally Consistent Decisions When Computing Costs with Limited Information. *Production and Operations Management, 26*(2), 211-230. doi:10.1111/poms.12631

Anand, V., Balakrishnan, R., & Labro, E. (2019). A Framework for Conducting Numerical Experiments on Cost System Design. *Journal of Management Accounting Research, 31*(1), 41-61. doi:10.2308/jmar-52057

Anderson, M. C., Banker, R. D., & Janakiraman, S. N. (2003). Are Selling, General, and Administrative Costs "Sticky"? *Journal of Accounting Research, 41*(1), 47-63. doi:10.1111/1475-679x.00095

Anderson, S. W. (1995). Measuring the Impact of Product Mix Heterogeneity on Manufacturing Overhead Cost. *The Accounting Review, 70*(3), 363-387.

Anderson, S. W. (2006). Managing Costs and Cost Structure throughout the Value Chain: Research on Strategic Cost Management. In C. S. Chapman, A. G. Hopwood, & M. D. Shields (Eds.), *Handbooks of Management Accounting Research* (Vol. 2, pp. 481-506). UK, Oxford, Linacre House: Elsevier.

Anderson, S. W., & Dekker, H. C. (2009a). Strategic Cost Management in Supply Chains, Part 1: Structural Cost Management. *Accounting Horizons, 23*(2), 201-220. doi:10.2308/acch.2009.23.2.201

Anderson, S. W., & Dekker, H. C. (2009b). Strategic Cost Management in Supply Chains, Part 2: Executional Cost Management. *Accounting Horizons, 23*(3), 289-305. doi:10.2308/acch.2009.23.3.289

Anderson, S. W., Hesford, J. W., & Young, S. M. (2002). Factors influencing the performance of activity based costing teams: a field study of ABC model development time in the automobile industry. *Accounting Organizations and Society, 27*(3), 195-211. doi:10.1016/S0361-3682(01)00057-5

Anderson, S. W., & Sedatole, K. (1998). Designing quality into products: The use of accounting data in new product development. *Accounting Horizons, 12*(3), 213-233.

Anderson, S. W., & Sedatole, K. L. (2013). Evidence on the Cost Hierarchy: The Association between Resource Consumption and Production Activities. *Journal of Management Accounting Research, 25*(1), 119-141. doi:10.2308/jmar-50293

Antle, R., & Demski, J. S. (1988). The Controllability Principle in Responsability Accounting. *The Accounting Review, 63*(4), 700-718.

Arend, R. J., Zhao, Y. L., Song, M., & Im, S. (2017). Strategic planning as a complex and enabling managerial tool. *Strategic Management Journal, 38*(8), 1741-1752. doi:10.1002/smj.2420

ASME. (2007). Guide for Verification and Validation in Computational Solid Mechanics. *American Socierty of Mechanical Engineers*. Retrieved from

Axelrod, R. (1997). *Advancing the Art of Simulation in the Social Sciences*. Germany, Heidelberg: Springer.

Axelrod, R. (Ed.) (2006). *Agent-based Modeling as a Bridge Between Disciplines* (Vol. 2): Elservier.

Babad, Y., & Balachandran, B. V. (1993). Cost drivers optimization in activity-based costing. *The Accounting Review, 68*(3), 563-575.

Baker, K. R., Magazine, M. J., & Nuttle, H. L. W. (1986). The Effect of Commonality on Safety Stock in a Simple Inventory Model. *Management science, 32*(8), 982-988. doi:10.1287/mnsc.32.8.982

Balachandran, B. V., Balakrishnan, R., & Sivaramakrishnan, K. (1997). On the efficiency of cost-based decision rules for capacity planning. *The Accounting Review, 72*(4), 599-619.

Balakrishnan, R., Hansen, S., & Labro, E. (2011). Evaluating heuristics used when designing product costing systems. *Management science, 57*(3), 520-541. doi:10.1287/mnsc.1100.1293

Balakrishnan, R., Labro, E., & Sivaramakrishnan, K. (2012a). Product Costs as Decision Aids: An Analysis of Alternative Approaches (Part 1). *Accounting Horizons, 26*(1), 1-20. doi:10.2308/acch-50086

Balakrishnan, R., Labro, E., & Sivaramakrishnan, K. (2012b). Product Costs as Decision Aids: An Analysis of Alternative Approaches (Part 2). *Accounting Horizons, 26*(1), 21-41. doi:10.2308/acch-10197

Balakrishnan, R., Labro, E., & Soderstrom, N. S. (2014). Cost Structure and Sticky Costs. *Journal of Management Accounting Research, 26*(2), 91-116. doi:10.2308/jmar-50831

Balakrishnan, R., & Penno, M. (2014). Causality in the context of analytical models and numerical experiments. *Accounting Organizations and Society, 39*(7), 531-534. doi:10.1016/j.aos.2013.09.004

Balakrishnan, R., & Sivaramakrishnan, K. (2002). A Critical Overview of the Use of Full-Cost Data for Planning and Pricing. *Journal of Management Accounting Research, 14*(1), 3-31. doi:10.2308/jmar.2002.14.1.3

Balci, O. (1994). Validation, Verification, and Testing Techniques Throughout the Life Cycle of a Simulation Study. *Annals of Operations Research, 53*, 121-173. doi:10.1007/BF02136828

Baldwin, C. Y., & Clark, K. B. (1997). Managing in an Age of Modularity. *Harvard Business Review, 75*(5), 84-93.

Baldwin, C. Y., & Clark, K. B. (2000). *Design Rules* (Vol. 1). USA, MA, Cambridge: The MIT Press.

Baldwin, C. Y., & Henkel, J. (2015). Modularity and intellectual property protection. *Strategic Management Journal, 36*(11), 1637-1655. doi:10.1002/smj.2303

Banker, R. D., Bardhan, I. R., & Chen, T.-Y. (2008). The role of manufacturing practices in mediating the impact of activity-based costing on plant performance. *Accounting, Organizations and Society, 33*(1), 1-19. doi:10.1016/j.aos.2006.12.001

Banker, R. D., Byzalov, D., Fang, S., & Liang, Y. (2018). Cost Management Research. *Journal of Management Accounting Research, 30*(3), 187-209. doi:10.2308/jmar-51965

Banker, R. D., & Datar, S. (1989). Sensitivity, Precision and Linear Aggregation of Linear Aggregation of Signals for Performance Evaluation. *Journal of Accounting Research, 27*(1), 21-39.

Banker, R. D., Datar, S., Kekre, S., & Mukhopadhyay, T. (1990). Costs of product and process complexity. In R. S. Kaplan (Ed.), *Measures for Manufacturing Excellence*. USA, MA, Boston: Havard Business School Press.

Banker, R. D., Datar, S. M., & Kekre, S. (1988). Relevant Costs, Congestion and Stochasticity in Production Environments. *Journal of Accounting & Economics, 10*(3), 171-197. doi:10.1016/0165-4101(88)90002-X

Banker, R. D., & Hughes, J. S. (1994). Product Costing and Pricing. *The Accounting Review, 69*(3), 479-494.

Banker, R. D., Hwang, I., & Mishra, B. K. (2002). Product Costing and Pricing under Long-Term Capacity Commitment. *Journal of Management Accounting Research, 14*(1), 79-97. doi:10.2308/jmar.2002.14.1.79

Banker, R. D., & Johnston, H. H. (1993). An empirical study of cost drivers in the U.S. airline industry. *The Accounting Review, 68*(3), 576-601.

Banker, R. D., & Johnston, H. H. (2006). Cost and profit driver research. In S. C. Christopher, A. G. Hopwood, & M. D. Shields (Eds.), *Handbooks of Management Accounting Research* (Vol. 2, pp. 531-556). UK, Oxford, Linacre House: Elsevier.

Banker, R. D., & Potter, G. (1993). Economic implications of single cost driver systems. *Journal of Management Accounting Research, 5*, 15-22.

Banker, R. D., Potter, G., & Schroeder, R. G. (1995). An Empirical-Analysis of Manufacturing Overhead Cost Drivers. *Journal of Accounting & Economics, 19*(1), 115-137. doi:10.1016/0165-4101(94)00372-C

Barth, R., Meyer, M., & Spitzner, J. (2012). Typical Pitfalls of Simulation Modeling - Lessons Learned from Armed Forces and Business. *Journal of Artificial Societies and Social Simulation, 15*(2). doi:10.18564/jasss.1935

Barton, R. R. (1998). Simulation Metamodeling. In D. J. Medeiros, E. F. Watson, J. S. Carson, & M. S. Manivannan (Eds.), *Proceedings of the 1998 Winter Simulation Conference* (pp. 167-174). USA, NJ, Piscataway: IEEE.

Barton, R. R. (2013). Designing Simulation Experiments. In S.-H. K. R. Pasupathy, A. Tolk, R. Hill, and M. E. Kuhl (Ed.), *Proceedings of the 2013 Winter Simulation Conference* (pp. 342-353). USA, NJ, Piscataway: IEEE.

Barton, R. R. (2015). Tutorial: Simulation Metamodeling. In L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. M. Macal, & M. Rosetti (Eds.), *Proceedings of the 2015 Winter Simulation Conference* (pp. 1765-1779). USA, NJ, Piscataway: IEEE.

Barton, R. R., & Meckesheimer, M. (2006). Metamodel-Based Simulation Optimization. In S. G. Henderson & B. I. Nelson (Eds.), *Handbooks in Operation Research and Management Science* (Vol. 13, pp. 535-570s). Netherlands, Amsterdam: Elsevier B.V.

Benabdellah, A. C., Bouhaddou, I., Benghabrit, A., & Benghabrit, O. (2019). A systematic review of design for X techniques from 1980 to 2018: concepts, applications, and perspectives. *The International Journal of Advanced Manufacturing Technology, 102*(9-12), 3473-3502. doi:10.1007/s00170-019-03418-6

Bersini, H. (2012). UML for ABM. *Journal of Artificial Societies and Social Simulation, 15*(1). doi:10.18564/jasss.1897

Bertoni, A., & Bertoni, M. (2018). PSS cost engineering: A model-based approach for concept design. *CIRP Journal of Manufacturing Science and Technology*. doi:10.1016/j.cirpj.2018.08.001

Birnbaum, P. H. (1981). Contingencies for Interdisciplinary Research: Matching Research Questions with Research Organizations. *Management science, 27*(11), 1279-1293. doi:10.1287/mnsc.27.11.1279

Blecker, T., Wilding, R., & Abdelkafi, N. (2006). Complexity and variety in mass customization systems: analysis and recommendations. *Management Decision, 44*(7), 908-929. doi:10.1108/00251740610680596

Blees, C. (2011). *Eine Methode zur Entwicklung modularer Produktfamilien*. Hamburg: TuTech Verlag Hamburg.

Blees, C., Joans, H., & Krause, D. (2010). *Development of modular product families.* Paper presented at the 12TH INTERNATIONAL DEPENDENCY AND STRUCTURE MODELLING CONFERENCE, DSM’10, 22 – 23 JULY 2010, CAMBRIDGE, UK.

Blocher, E., Stout, D., Juras, P., & Cokins, G. (2012). *Cost Management - A Strategic Emphasis* (Vol. 6th Edition). USA, NY, New York: McGraw-Hill Education.

Bloomfield, R. J. (2016). *What Counts and What Gets Counted*. USA, NY, Ithaca: Cornell University.

Bol, J. C., Kramer, S., & Maas, V. S. (2016). How control system design affects performance evaluation compression: The role of information accuracy and outcome transparency. *Accounting, Organizations and Society, 51*, 64-73. doi:10.1016/j.aos.2016.01.001

Boons, A. A. M., Roberts, H. J. E., & Roozen, F. A. (1992). Contrasting activity-based costing with the German/Dutch cost pool method. *Management Accounting Research, 3*(2), 97-117. doi:10.1016/s1044-5005(92)70006-7

Box, G. E. P. (1976). Science and Statistics. *Journal of the American Statistical Association, 71*(356), 791-799. doi:10.1080/01621459.1976.10480949

Brierley, J. A. (2008). Toward an Understanding of the Sophistication of Product Costing Systems. *Journal of Management Accounting Research, 20*(1), 61-78. doi:10.2308/jmar.2008.20.s-1.61

Brusoni, S., & Prencipe, A. (2011). Patterns of Modularization: The Dynamics of Product Architecture in Complex Systems. *European Management Review, 8*(2), 67-80. doi:10.1111/j.1740-4762.2011.01010.x

Cagwin, D., & Bouwman, M. J. (2002). The association between activity-based costing and improvement in financial performance. *Management Accounting Research, 13*(1), 1-39. doi:10.1006/mare.2001.0175

Calleja, K., Steliaros, M., & Thomas, D. C. (2006). A note on cost stickiness: Some international comparisons. *Management Accounting Research, 17*(2), 127-140. doi:10.1016/j.mar.2006.02.001

Campagnolo, D., & Camuffo, A. (2010). The concept of modularity in management studies: A literature review. *International Journal of Management Reviews, 12*(3), 259-283. doi:10.1111/j.1468-2370.2009.00260.x

Cardinaels, E., & Labro, E. (2008). On the determinants of measurement error in time-driven costing. *The Accounting Review, 83*(3), 735-756. doi:10.2308/accr.2008.83.3.735

Cebi, S., & Kahraman, C. (2010). Extension of axiomatic design principles under fuzzy environment. *Expert Systems with Applications, 37*(3), 2682-2689. doi:10.1016/j.eswa.2009.08.010

Chan, L.-K., & Wu, M.-L. (2002). Quality function deployment: A literature review. *European Journal of Operational Research, 143*(3), 463-497. doi:10.1016/s0377-2217(02)00178-9

Chapman, C. S., & Kihn, L.-A. (2009). Information system integration, enabling control and performance. *Accounting, Organizations and Society, 34*(2), 151-169. doi:10.1016/j.aos.2008.07.003

Child, P., Diederichs, R., Sanders, F.-H., Wisniowski, S., & Cummings, P. (1991). SMR forum: the management of complexity. *Sloan management review, 33*(1), 73-81.

Christensen, J. (2010). Accounting Errors and Errors of Accounting. *The Accounting Review, 85*(6), 1827-1838. doi:10.2308/accr.2010.85.6.1827

Christensen, J., & Demski, J. S. (1995). The classical foundations of 'modern' costing. *Management Accounting Research, 6*(1), 13-32.

Christensen, J., & Demski, J. S. (1997). Product costing in the presence of endogenous subcost functions. *Review of Accounting Studies, 2*, 65-87.

Christensen, J., & Demski, J. S. (2003). Factor Choice Distortion under Cost-Based Reimbursement. *Journal of Management Accounting Research, 15*(1), 145-160. doi:10.2308/jmar.2003.15.1.145

Christensen, J., & Hemmer, T. (2006). Analytical Modeling of Cost in Management Accounting Research. In C. S. Chapman, A. G. Hopwood, & M. D. Shields (Eds.), *Handbook of Management Accounting Research* (Vol. 2, pp. 557-571): Elsevier Ltd.

Cinquini, L., Collini, P., Marelli, A., & Tenucci, A. (2013). Change in the relevance of cost information and costing systems: evidence from two Italian surveys. *Journal of Management & Governance, 19*(3), 557-587. doi:10.1007/s10997-013-9275-4

Clymer, J. R. (2009). *Simulation-based engineering of complex systems*. USA, NJ, Hoboken John Wiley & Sons, Inc. .

Cobb, C. W., & Douglas, P. H. (1928). A Theory of Production. *American Economic Review, 18*(1), 139-165.

Coenenberg, A. G., Fischer, T. M., & Günther, T. (2012). *Kostenrechnung und Kostenanalyse*. Germany, Stuttgart: Schäffer-Poeschel Verlag

Collier, D. A. (1981). The Measurement and Operating Benefits of Component Part Commonality. *Decision Sciences, 12*(1), 85-96. doi:10.1111/j.1540-5915.1981.tb00063.x

Conte, R. (2009). From Simulation to Theory (and Backward). In F. Squazzoni (Ed.), *Epistemological Aspects of Computer Simulation in the Social Sciences* (pp. 29-47). Berlin, Heidelberg: Springer.

Cook, H. E., & Wissmann, L. A. (2007). *Value Driven Product Planning and Systems Engineering*. UK, London: Springer.

Cooper, D. J., & Hopper, T. (Eds.). (2006). *Critical Theorising in Management Accounting Research* (Vol. 1). UK, Oxford, Linacre House: Elsevier.

Cooper, R. (1989). You need a new cost system when... *Harvard Business Review, 67*, 77-82.

Cooper, R. (1990). Cost classification in unit-based and activity-based manufacturing industry. *Journal of Cost Management for the manufacturing industry, 4*(3), 4-14.

Cooper, R., & Kaplan, R. S. (1987). How cost accounting distorts product costs. *Management Accounting, 69*(10), 20-27.

Cooper, R., & Kaplan, R. S. (1988). Measure costs right: make the right decisions. *Harvard Business Review, 66*(5), 96-103.

Cooper, R., & Kaplan, R. S. (1991). Profit priorities from activity-based costing. *Harvard Business Review, 69*, 130-135.
Cooper, R., & Kaplan, R. S. (1992). Activity-based systems: measuring the costs of resource usage. *Accounting Horizons, 6*(3), 1-13.
Cooper, R., & Kaplan, R. S. (1998a). *Cost and Effect: Using Integrated Cost Systemss to Drive Profitability and Performance*. USA, MA, Cambridge: HBS Press.
Cooper, R., & Kaplan, R. S. (1998b). *Design of cost management systems: text and cases* (Vol. 2). USA, NJ, Englewood Cliffs: Prentice Hall, Inc.
D'aveni, R. A. (2010). *Hypercompetition*: Simon and Schuster.
Danese, P., & Filippini, R. (2013). Direct and Mediated Effects of Product Modularity on Development Time and Product Performance. *IEEE Transactions on Engineering Management, 60*(2), 260-271. doi:10.1109/tem.2012.2208268
Danilovic, M., & Browning, T. R. (2007). Managing complex product development projects with design structure matrices and domain mapping matrices. *International Journal of Project Management, 25*(3), 300-314. doi:10.1016/j.ijproman.2006.11.003
Datar, S., & Gupta, M. (1994). Aggregation, specification and measurement errors in product costing. *The Accounting Review, 69*(4), 567-591.
Datar, S., Kekre, S., Mukhopadhyay, T., & Srinivasan, K. (1993). Simultaneous estimation of cost drivers. *The Accounting Review, 68*(3), 602-614.
Datar, S., Kulp, S. C., & Lambert, R. A. (2001). Balancing Performance Measures. *Journal of Accounting Research, 39*(1), 75-92. doi:10.1111/1475-679x.00004
Davila, T., & Wouters, M. (2004). Designing Cost-Competitive Technology Products through Cost Management. *Accounting Horizons, 18*(1), 13-26. doi:10.2308/acch.2004.18.1.13
Davila, T., & Wouters, M. (2006). Management Accounting in the Manufacturing Sector: Managing Costs at the Design and Production Stages. *2*, 831-858. doi:10.1016/s1751-3243(06)02015-3
Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review, 32*(2), 480-499. doi:10.5465/amr.2007.24351453
Demski, J. S. (2008). *Managerial Uses of Accounting Information* (Vol. 2). New York, NY, USA: Springer Science+Business Media.
Desai, P., Kekre, S., Radhakrishnan, S., & Srinivasan, K. (2001). Product Differentiation and Commonality in Design: Balancing Revenue and Cost Drivers. *Management science, 47*(1), 37-51. doi:10.1287/mnsc.47.1.37.10672
Dikolli, S. S., & Sedatole, K. L. (2007). Improvements in the Information Content of Nonfinancial Forward-Looking Performance Measures: A Taxonomy and Empirical Application. *Journal of Management Accounting Research, 19*(1), 71-104. doi:10.2308/jmar.2007.19.1.71
DIN1319-1. (1995-01). Fundamental of metrology - Part 1: Basic terminology. Retrieved from https://www.beuth.de/en/standard/din-1319-1/2440447 doi:10.31030/2713411
Dopuch, N. (1993). A Perspective on Cost Drivers. *The Accounting Review, 68*(3), 615-620.
Drury, C. (2009). *Management Accounting for Business*. UK, Hampshire: Cengage Learning EMEA.
Drury, C. (2015). *Cost and Management Accounting - An Introduction* (Vol. 8th Edition). UK, Andover: Cengage Learning
Drury, C., & Tayles, M. (1994). Product costing in UK manufacturing organizations. *European Accounting Review, 3*(3), 443-470. doi:10.1080/09638189400000031
Drury, C., & Tayles, M. (2005). Explicating the design of overhead absorption procedures in UK organizations. *The British Accounting Review, 37*(1), 47-84. doi:10.1016/j.bar.2004.08.003

Du, X., Jiao, J., & Tseng, M. M. (2001). Architecture of product family: Fundamentals and methodology. *Concurrent Engineering: Research and Application 9*(4), 309-325. doi:10.1177/1063293X0100900407

Du, X., Jiao, J., & Tseng, M. M. (2005). Understanding customer satisfaction in product customization. *The International Journal of Advanced Manufacturing Technology, 31*(3-4), 396-406. doi:10.1007/s00170-005-0177-8

Edmonds, B., & Moss, S. (2005). From KISS to KIDS – an 'anti-simplistic' modeling approach. In P. Davidsson & B. Logan (Eds.), *Multi Agent Based Simulation* (Vol. 3415). Germany, Heidelberg: Springer.

Efatmaneshnik, M., Shoval, S., & Qiao, L. (2018). A Standard Description of the Terms Module and Modularity for Systems Engineering. *IEEE Transactions on Engineering Management*, 1-11. doi:10.1109/tem.2018.2878589

Ehrlenspiel, K., Kiewert, A., & Lindemann, U. (2002). Zielkostenorientierte Produktentwicklung. In K.-P. Franz & P. Kajüter (Eds.), *Kostenmanagement - Wertsteigerung durch systematische Kostensteuerung*. Germany, Berlin: Schäffer Poeschel.

Ehrlenspiel, K., Kiewert, A., Lindemann, U., & Mörtl, M. (2014). *Kostengünstig Entwickeln und Konstruieren* (Vol. 7). Germany, Heidelberg: Springer Verlag.

Eigner, M., Roubanov, D., & Zafirov, R. (Eds.). (2014). *Modellbasierte virtuelle Produktentwicklung*. Germany, Berlin: Springer Verlag.

Einstein, A. (1905). Does the Inertia of a Body Depend upon its Energy Content? *Annalen der Physik, 18*, 639-641.

ElMaraghy, W., ElMaraghy, H., Tomiyama, T., & Monostori, L. (2012). Complexity in engineering design and manufacturing. *Cirp Annals-Manufacturing Technology, 61*(2), 793-814. doi:10.1016/j.cirp.2012.05.001

Eppinger, S. D., & Browning, T. R. (2012). *Design structure matrix methods and applications*. USA, MA, Cambridge: MIT Press.

Eppinger, S. D., Whitney, D. E., Smith, R. P., & Gebala, D. (1994). A Model-Based Method for Organizing Tasks in Product Development *Research in Engineering Design, 6*, 1-13.

Epstein, J. M. (2008). Why Model? *Journal of Artificial Societies and Social Simulation, 11*(4), 12.

Erb, C., & Pelger, C. (2015). "Twisting words"? A study of the construction and reconstruction of reliability in financial reporting standard-setting. *Accounting, Organizations and Society, 40*, 13-40. doi:10.1016/j.aos.2014.11.001

Erens, F., & Verhulst, K. (1997). Architectures for product families. *Computers in Industry, 33*(2-3), 165-178. doi:10.1016/s0166-3615(97)00022-5

Erixon, G. (1998). *Modular function deployment*: Institutionen för produktionssystem.

Ethiraj, S. K., & Levinthal, D. (2004). Modularity and Innovation in Complex Systems. *Management science, 50*(2), 159-173. doi:10.1287/mnsc.1030.0145

Evans, M. R., Grimm, V., Johst, K., Knuuttila, T., de Langhe, R., Lessells, C. M., . . . Benton, T. G. (2013). Do simple models lead to generality in ecology? *Trends Ecol Evol, 28*(10), 578-583. doi:10.1016/j.tree.2013.05.022

Fandel, G. (2005). *Produktion I - Produktions- und Kostentheorie* (Vol. 6). Germany, Heidelberg: Springer.

Farrell, R. S., & Simpson, T. W. (2009). Improving cost effectiveness in an existing product line using component product platforms. *International Journal of Production Research, 48*(11), 3299-3317. doi:10.1080/00207540802620753

FASB. (2010). *Conceptual Framework of Financial Reporting* Retrieved from https://www.fasb.org/resources/ccurl/515/412/Concepts%20Statement%20No%208.pdf

Feitzinger, E., & Lee, H. L. (1997). Mass customization at Hewlett-Packard: the power of postponement. *Harvard Business Review, 75*, 116-123.

Feltham, G. A. (1977). Cost aggregation: An information economic analysis. *Journal of Accounting Research, 15*(1), 42-70.

Feltham, G. A., & Xie, J. (1994). Performance Measure Congruity and Diversity in Multi-Task Principal/Agent Relations. *The Accounting Review, 69*(3), 429-453.

Fisher, M., Ramdas, K., & Ulrich, K. (1999). Component Sharing in the Management of Product Variety: A Study of Automotive Braking Systems. *Management science, 45*(3), 297-315. doi:10.1287/mnsc.45.3.297

Fixson, S. K. (2005). Product architecture assessment: a tool to link product, process, and supply chain design decisions. *Journal of Operations Management, 23*(3-4), 345-369. doi:10.1016/j.jom.2004.08.006

Fixson, S. K. (2006). A roadmap for product architecture costing. In T. W. Simpson, Z. Siddique, & J. Jiao (Eds.), *Product Platform and Product Family Design* (Vol. 1). USA, NY, New York: Springer.

Fixson, S. K. (2007). Modularity and commonality research: past developments and future opportunities. *Concurrent Engineering-Research and Applications, 15*(2), 85-111. doi:10.1177/1063293x07078935

Foster, G., & Gupta, M. (1990). Manufacturing Overhead Cost Driver Analysis. *Journal of Accounting & Economics, 12*(1-3), 309-337. doi:10.1016/0165-4101(90)90052-6

Frandsen, T. (2017). Evolution of modularity literature: a 25-year bibliometric analysis. *International Journal of Operations & Production Management, 37*(6), 703-747. doi:10.1108/ijopm-06-2015-0366

Franz, K.-P., & Kajüter, P. (2002). *Kostenmanagement - Wettbewerbsvorteile durch systematische Kostensteuerung.* (Vol. 2). Germany, München: Schäffer Poeschel.

Fuchs, E., & Kirchain, R. (2010). Design for Location? The Impact of Manufacturing Offshore on Technology Competitiveness in the Optoelectronics Industry. *Management science, 56*(12), 2323-2349. doi:10.1287/mnsc.1100.1227

Galsworth, G. D. (1994). *Smart, simple design: using variety effectiveness to reduce total cost and maximize customer selection*: Omneo.

Gerchak, Y., Magazine, M. J., & Gamble, A. B. (1988). Component Commonality with Service Level Requirements. *Management science, 34*(6), 753-760. doi:10.1287/mnsc.34.6.753

Gershenson, J. K., Prasad, G. J., & Zhang, Y. (2003). Product modularity: Definitions and benefits. *Journal of Engineering Design, 14*(3), 295-313. doi:10.1080/0954482031000091068

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: frequency formats. *Psychological review, 102*(4), 684. doi:10.1037/0033-295X.102.4.684

Gonçalves-Coelho, A. M., & Mourão, A. J. F. (2007). Axiomatic design as support for decision-making in a design for manufacturing context: A case study. *International Journal of Production Economics, 109*(1-2), 81-89. doi:10.1016/j.ijpe.2006.11.002

Göpfert, J. (1998). *Modulare Produktentwicklung*. Germany, München: Gabler Edition Wissenschft.

Gore, R., Diallo, S., Lynch, C., & Padilla, J. J. (2017). Augmenting Bottom-Up Metamodels with Predicates. *Journal of Artificial Societies and Social Simulation, 20*(1). doi:10.18564/jasss.3240

Gosselin, M. (1997). The effect of strategy and organizational structure on the adoption and implementation of activity-based costing. *Accounting Organizations and Society, 22*(2), 105-122. doi:10.1016/S0361-3682(96)00031-1

Gosselin, M. (2006). A Review of activity-based costing: technique, implementation, and consequences. In S. C. Christopher, A. G. Hopwood, & M. D. Shields (Eds.), *Handbook of Management Accounting Research* (Vol. 2, pp. 641-671): Elsevier Ltd.

Gow, I. D., Larcker, D. F., & Reiss, P. C. (2016). Causal Inference in Accounting Research. *Journal of Accounting Research, 54*(2), 477-523. doi:10.1111/1475-679x.12116

Grabe, M. (2014). *Measurement Uncertainties in Science and Technology* (Vol. 2nd Edition). Germany, Heidelberg: Springer.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling, 221*(23), 2760-2768. doi:10.1016/j.ecolmodel.2010.08.019

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., . . . DeAngelis, D. L. (2005). Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *Science, 310*(5750), 987-991. doi:10.1126/science.1116681

Grisar, C., & Meyer, M. (2015). Use of Monte Carlo simulation: an empirical study of German, Austrian and Swiss controlling departments. *Journal of Management Control, 26*(2-3), 249-273. doi:10.1007/s00187-015-0213-2

Gu, P., & Sosale, S. (1999). Product modularization for life cycle engineering. *Robotics and Computer-Integrated Manufacturing, 15*(5), 387-401. doi:10.1016/s0736-5845(99)00049-6

Guenov, M. D. (2002). *Complexity and Cost Effectiveness Measure for Systems Design.* Paper presented at the Manufacturing Complexity Network Conference, Downing College, Cambride, UK.

Guenov, M. D., & Barker, S. G. (2005). Application of axiomatic design and design structure matrix to the decomposition of engineering systems. *Systems Engineering, 8*(1), 29-40. doi:10.1002/sys.20015

Guenther, T. W., Riehl, A., & Rößler, R. (2014). Cost stickiness: state of the art of research and implications. *Journal of Management Control, 24*(4), 301-318. doi:10.1007/s00187-013-0176-0

Gumus, B. (2005). *Axiomatic product development lifecycle.* (Ph.D.), Texas Tech University USA, TX.

Gupta, M. (1993). Heterogeneity issues in aggregated costing systems. *Journal of Management Accounting Research, 5*, 180-212.

Hackl, J., Krause, D., Otto, K., Windheim, M., Moon, S. K., Bursac, N., & Lachmayer, R. (2020). Impact of Modularity Decisions on a Firm's Economic Objectives. *Journal of Mechanical Design, 142*(4), 1-41. doi:10.1115/1.4044914

Halman, J. I. M., Hofer, A. P., & van Vuuren, W. (2003). Platform-Driven Development of Product Families: Linking Theory with Practice. *Journal of Product Innovation Management, 20*(2), 149-162. doi:10.1111/1540-5885.2002007

Hanemann, M. (1991). Willingness To Pay and Willingness To Accept: How Much Can They Differ? *American Economic Review, 81*(3), 635-647.

Hansen, D. R., & Mowen, M. M. (2006). *Managerial Accounting* (Vol. 8). USA, MA, Boston: Cengage Learning.

Harrison, J. R., Lin, Z., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review, 32*(4), 1229-1245. doi:10.5465/AMR.2007.26586485

Hauke, J., Lorscheid, I., & Meyer, M. (2017a). Individuals and their interactions in demand planning processes: an agent-based, computational testbed. *International Journal of Production Research, 56*(13), 4644-4658. doi:10.1080/00207543.2017.1377356

Hauke, J., Lorscheid, I., & Meyer, M. (2017b). Recent Development of Social Simulation as Reflected in JASSS Between 2008 and 2014: A Citation and Co-Citation Analysis. *Journal of Artificial Societies and Social Simulation, 20*(1). doi:10.18564/jasss.3238

Hazelrigg, G. A. (1998). A framework for decision-based engineering design. *Journal of Mechanical Design, 120*(4), 653-658. doi:10.1115/1.2829328

Henderson, R. M., & Clark, K. B. (1990). Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly, 35*(1), 9. doi:10.2307/2393549

Hinkelmann, K., & Kempthorne, O. (2012). *Design and Analysis of Experiments Vol. 1* (Auflage Ed. Vol. 1). Hoboken, New Jersey: John Wiley & Sons Inc.

Hogarth, R. M., & Einhorn, H. J. (1992). Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology, 24*(1), 1-55. doi:10.1016/0010-0285(92)90002-j

Hölmstrom, B. (1979). Moral Hazard and Observability. *The Bell Journal of Economics, 10*(1), 74. doi:10.2307/3003320

Hölmstrom, B. (1982). Moral Hazard in Teams. *The Bell Journal of Economics, 13*(2), 324-340. doi:10.2307/3003457

Hölttä-Otto, K. (2005). *Modular product platform design*: Helsinki University of Technology.

Hölttä-Otto, K., & de Weck, O. (2007). Degree of Modularity in Engineering Systems and Products with Technical and Business Constraints. *Concurrent Engineering, 15*(2), 113-126. doi:10.1177/1063293x07078931

Hölttä-Otto, K., Otto, K. N., & Simpson, T. W. (2014). Defining Modules for Platforms: An Overview of the Architecting Process. In T. W. Simpson, J. Jiao, Z. Siddique, & K. Hölttä-Otto (Eds.), *Advances in Product Family and Product Platform Design: Methods & Applications* (pp. 323-341). New York, NY: Springer New York.

Homburg, C. (2001). A note on optimal cost driver selection in ABC. *Management Accounting Research, 12*(2), 197-205. doi:10.1006/mare.2000.0150

Homburg, C., Nasev, J., & Plank, P. (2017). The impact of cost allocation errors on price and product-mix decisions. *Review of Quantitative Finance and Accounting, 51*(2), 497-527. doi:10.1007/s11156-017-0678-1

Homburg, C., & Richter, M. (2002). Die Analyse von Kostenproblemen. In K.-P. Franz & P. Kajüter (Eds.), *Kostenmanagement - Wertsteigerung durch systematische Kostensteuerung*: Schäffer Poeschel.

Homburg, C., & Stock-Homburg, R. (2012). Theoretische Perspektiven zur Kundenzufriedenheit. In C. Homburg (Ed.), *Kundenzufriedenheit - Konzepte - Methoden - Erfahrungen* (Vol. 8. Auflage, pp. 17-53). Wiesbaden: Gabler Verlag.

Hoozée, S., & Hansen, S. (2018). A Comparison of Activity-Based Costing and Time-Driven Activity-Based Costing. *Journal of Management Accounting Research, 30*(1), 143-167. doi:10.2308/jmar-51686

Hoozée, S., Vermeire, L., & Bruggeman, W. (2012). The Impact of Refinement on the Accuracy of Time-driven ABC. *Abacus, 48*(4), 439-472. doi:10.1111/j.1467-6281.2012.00366.x

Horngren, C. T., Datar, S., & Raja, M. V. (2014). *Cost Accounting A Managerial Emphasis* (Vol. 15). USA, NJ, Upper Saddle River: Prentice Hall Inc.

Hsuan, J. (1999). Impacts of supplier–buyer relationships on modularization in new product development. *European Journal of Purchasing & Supply Management, 5*(3-4), 197-209.

Hundal, M. S. (1997). Product Costing: A Comparison of Conventional and Activity-based Costing Methods. *Journal of Engineering Design, 8*(1), 91-103. doi:10.1080/09544829708907954

Hwang, Y., Evans, J. H., & Hegde, V. G. (1993). Product cost bias and selection of an allocation base. *Journal of Management Accounting Research, 5*, 213-242.

Hwang, Y., & Kirby, A. J. (1994). Distorted Mediacare Reimbursements: The Effect of Cost ACcounting Choices. *Journal of Management Accounting Research, 6*, 128-143.
IAASB. (2008). *International Standard on Auditing (ISA) 540: Auditing accounting estimates, including fair value accounting estimates, and related disclosures*. USA, NY, New York: IAASB.
IASB. (2018). Conceptual Framework for Financial Reporting 2018. Retrieved from https://app1.hkicpa.org.hk/hksaebk/HKSA_Members_Handbook_Master/volumeII/framework18.pdf
Iman, N. (2016). Modularity matters: a critical review and synthesis of service modularity. *International Journal of Quality and Service Sciences, 8*(1), 38-52. doi:10.1108/ijqss-05-2015-0046
Israelsen, P., & Jørgensen, B. (2011). Decentralizing decision making in modularization strategies: Overcoming barriers from dysfunctional accounting systems. *International Journal of Production Economics, 131*(2), 453-462. doi:10.1016/j.ijpe.2010.12.020
Ittner, C. D., Lanen, W. N., & Larcker, D. F. (2002). The association between activity-based costing and manufacturing performance. *Journal of Accounting Research, 40*(3), 711-726. doi:10.1111/1475-679x.00068
Ittner, C. D., Larcker, D. F., & Randall, T. (1997). The activity-based cost hierarchy, production policies and firm profitability. *Journal of Management Accounting Research, 9*, 143-162.
Jacobs, M., Droge, C., Vickery, S. K., & Calantone, R. (2011). Product and Process Modularity's Effects on Manufacturing Agility and Firm Growth Performance. *Journal of Product Innovation Management, 28*(1), 123-137. doi:10.1111/j.1540-5885.2010.00785.x
Jacobs, M., Vickery, S. K., & Droge, C. (2007). The effects of product modularity on competitive performance. *International Journal of Operations & Production Management, 27*(10), 1046-1068. doi:10.1108/01443570710820620
JCGM. (2008). 100 - Guide to the expression of uncertainty in measurement *Joint Committee for Guides in Metrology: Evaluation of measurement data*.
Jiao, J., Simpson, T. W., & Siddique, Z. (2007). Product family design and platform-based product development: a state-of-the-art review. *Journal of Intelligent Manufacturing, 18*(1), 5-29. doi:10.1007/s10845-007-0003-2
Jiao, J., & Tseng, M. M. (1999). A methodology of developing product family architecture for mass customization. *Journal of Intelligent Manufacturing, 10*(1), 3-20. doi:10.1023/A:1008926428533
Jiao, J., & Tseng, M. M. (2000). Fundamentals of product family architecture. *Integrated Manufacturing Systems, 11*(7), 469-483. doi:10.1108/09576060010349776
John, J. (2016). *Product cost controlling with SAP* (Vol. 3). Germany, Bonn: Rheinwerk Publishing.
Jonas, H., Gebhardt, N., & Krause, D. (2012). *Towards a strategic development of modular product programs*. Paper presented at the *International Design Conference - Design 2012*, Dubrovnik, Croatia.
Jones, T. C., & Dugdale, D. (2002). The ABC bandwagon and the juggernaut of modernity. *Accounting Organizations and Society, 27*(1-2), 121-163. doi:10.1016/S0361-3682(01)00035-6
Jose, A., & Tollenaere, M. (2005). Modular and platform methods for product family design: literature analysis. *Journal of Intelligent Manufacturing, 16*(3), 371-390. doi:10.1007/s10845-005-7030-7
Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal*

of Operations & Production Management, 37(1), 10-36. doi:10.1108/ijopm-02-2015-0078
Kallunki, J. P., & Silvola, H. (2008). The effect of organizational life cycle stage on the use of activity-based costing. *Management Accounting Research, 19*(1), 62-79. doi:10.1016/j.mar.2007.08.002
Kaplan, R., & Anderson, S. R. (2003). Time-driven activity-based costing. *Harvard Business Press*. doi:10.2139/ssrn.485443
Kaplan, R., & Anderson, S. R. (2007). *Time-driven activity-based costing: a simpler and more powerful path to higher profits*. USA, MA, Boston: Harvard Business Press.
Kekre, S., & Srinivasan, K. (1990). Broader Product Line: A Necessity to Achieve Success? *Management science, 36*(10), 1216-1232. doi:10.1287/mnsc.36.10.1216
Kennedy, T., & Affleck-Graves, J. (2001). The Impact of Activity-Based Costing Techniques on Firm Performance. *Journal of Management Accounting Research, 13*(1), 19-45. doi:10.2308/jmar.2001.13.1.19
Kersten, W., Seiter, M., Von See, B., Hackius, N., & Maurer, T. (2017). Trends und Strategien in Logistik und Supply Chain Management - Chancen der digitalen Transformation. *Bundesvereinigung Logistik (BVL)*.
Kersten, W., von See, B., Skirde, H., & Wichmann, M. (2015). *Schlussbericht zum Projekt "Bewertung von Komplexitätskosten in Logistiksystemen"*. IGF-Vorhaben 17726 N der Forschungsvereining Bundesvereinigung Logistik (BVL).
Kim, K., & Chhajed, D. (2000). Commonality in product design: Cost saving, valuation change and cannibalization. *European Journal of Operational Research, 125*(3), 602-621. doi:10.1016/s0377-2217(99)00271-4
Kipp, T. (2012). *Methodische Unterstützung der variantengerechten Produktgestaltung*. Germany, Hamburg: TuTech Verlag Hamburg.
Kleijnen, J. P. C. (2015). *Design and Analysis of Simulation Experiments* (Vol. Second Edition). Cham, CH: Springer International Publishing.
Kleijnen, J. P. C., & Sargent, R. G. (2000). A methodology for fitting and validating metamodels in simulation. *European Journal of Operational Research, 120*(1), 14-29. doi:10.1016/S0377-2217(98)00392-0
Klügel, F., & Karlsson, L. (2009). Towards Pattern-Oriented Design of Agent-Based Simulation Models. In Braubach, v. d. Hoek, Petta, & Pokahr (Eds.), *Multiagent System Technologies*.
Kota, S., Sethuraman, K., & Miller, R. (2000). A metric for evaluating design commonality in product families. *Journal of Mechanical Design, 122*(4), 403-410. doi:10.1115/1.1320820
Kotler, P., & Keller, K. (2015). *Marketing management - Global Edition* (Vol. 15). UK, Harlow: Pearson Education Limited.
Krause, D. (2012). Modulare Produktstrukturiering *Handbuch Konstruktion* (pp. 657-678). Germany, München: Hanser.
Krause, D., Beckmann, G., Eilmus, S., Gebhardt, N., Jonas, H., & Rettberg, R. (2014). Integrated Development of Modular Product Families: A Methods Toolkit. In T. W. Simpson, J. Jiao, Z. Siddique, & K. Höltta-Otto (Eds.), *Advances in Product Family and Product Platform Design - Methods & Applications*. Germany, Heidelberg: Springer.
Krause, D., & Gebhardt, N. (2018). *Methodische Entwicklung modularer Produktfamilien - Hohe Produktvielfalt beherrschbar entwickeln*. Germany, Berlin: Springer Verlag.
Krishnan, R. (2015). Management Accountant—What Ails Thee? *Journal of Management Accounting Research, 27*(1), 177-191. doi:10.2308/jmar-10461
Krishnan, R., Luft, J. L., & Shields, M. D. (2005). Effects of accounting-method choices on subjective performance-measure weighting decisions: Experimental evidence on

precision and error covariance. *The Accounting Review, 80*(4), 1163-1192. doi:DOI 10.2308/accr.2005.80.4.1163

Krishnan, V., & Gupta, S. (2001). Appropriateness and Impact of Platform-Based Product Development. *Management science, 47*(1), 52-68. doi:10.1287/mnsc.47.1.52.10665

Krumwiede, K. R., & Charles, S. L. (2014). The Use of Activity-based Costing with Competitive Strategies: Impact on Firm Performance. *Advances in Management Accounting, 23*, 113-148. doi:10.1108/S1474-787120140000023004

Kulak, O., Cebi, S., & Kahraman, C. (2010). Applications of axiomatic design principles: A literature review. *Expert Systems with Applications, 37*(9), 6705-6717. doi:10.1016/j.eswa.2010.03.061

Kumar, D., Chen, W., & Simpson, T. W. (2008). A market-driven approach to product family design. *International Journal of Production Research, 47*(1), 71-104. doi:10.1080/00207540701393171

Kuratowski, K., & Mostowski, A. (1976). Chapter II Axioms of Set Theory, Relations, Functions. In K. Kuratowski & A. Mostowski (Eds.), *Studies in Logic and the Foundations of Mathematics* (Vol. 86, pp. 46-88): Elsevier.

Labro, E. (2004). The Cost Effects of Component Commonality: A Literature Review Through a Management-Accounting Lens. *Manufacturing & Service Operations Management, 6*(4), 358-367. doi:10.1287/msom.1040.0047

Labro, E. (2006). Analytics of costing system design. In A. Bhimani (Ed.), *Contemporary issues in management accounting* (pp. 217-243). UK, Oxford: Oxford University Press.

Labro, E. (2019). Costing Systems. *Foundations and Trends® in Accounting, 13*(3-4), 267-404. doi:10.1561/1400000058

Labro, E., & Dierynck, B. (2018). Management Accounting Information Properties and Operations Management. *Foundations and Trends® in Technology, Information and Operations Management, 12*(1), 1-114. doi:10.1561/0200000051

Labro, E., & Vanhoucke, M. (2007). A simulation analysis of interactions among errors in costing systems. *The Accounting Review, 82*(4), 939-962. doi:10.2308/accr.2007.82.4.939

Labro, E., & Vanhoucke, M. (2008). Diversity in resource consumption patterns and robustness of costing systems to errors. *Management science, 54*(10), 1715-1730. doi:10.1287/mnsc.1080.0885

Lai, X., & Gershenson, J. K. (2007). Representation of similarity and dependency for assembly modularity. *The International Journal of Advanced Manufacturing Technology, 37*(7-8), 803-827. doi:10.1007/s00170-007-1010-3

Lanen, W. N., Anderson, S. W., & Maher, M. W. (2013). *Fundamentals of Cost Accounting* (Vol. 4th edition). USA, NY, New York: McGraw-Hill Education.

Law, A. M. (2014a). *Simulation Modeling and Analysis* (Vol. 5th International Edition). USA, NY, New York: McGraw-Hill, Inc.

Law, A. M. (2014b). A Tutorial on Design of Experiments for Simulation Modeling. In A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, & a. J. A. Miller (Eds.), *Proceedings of the 2014 Winter Simulation Conference* (pp. 66-80). USA, NJ, Piscataway: IEEE.

Lei, N., & Moon, S. K. (2015). A Decision Support System for market-driven product positioning and design. *Decision Support Systems, 69*, 82-91. doi:10.1016/j.dss.2014.11.010

Lewis, B., Shields, M. D., & Young, S. M. (1983). Evaluating Human Judgments and Decision Aids. *Journal of Accounting Research, 21*(1), 271. doi:10.2307/2490947

Li, J., & Meerkov, S. M. (2009). *Production Systems Engineering*. Germany, Heidelberg: Springer.

Libby, R. (1981). *Accounting and human information processing: theory and applictions*. USA, NJ, Englewood Cliffs: Prentice-Hall.

Libby, R., Bloomfield, R., & Nelson, M. W. (2002). Experimental research in financial accounting. *Accounting, Organizations and Society, 27*(8), 775-810. doi:10.1016/s0361-3682(01)00011-3

Lindemann, U., Maurer, M., & Braun, T. (2009). *Structural Complexity Management - An approach for the Field of Product design*. Germany, Berlin: Springer-Verlag.

Little, J. D. C., & Graves, S. C. (2008). Little's Law. In D. Chhajed & T. J. Lowe (Eds.), *Building Intuition: Insights From Basic Operations Management Models and Principles* (pp. 81-100). USA, MA, Boston: Springer US.

Lorscheid, I., Heine, B.-O., & Meyer, M. (2012). Opening the 'Black Box' of Simulations: Increased Transparency and Effective Communication through the systematic Design of Experiments. *Computational and Mathematical Organization Theory, 18*(1), 22-62.

Luchs, M., & Swan, K. S. (2011). Perspective: The Emergence of Product Design as a Field of Marketing Inquiry. *Journal of Product Innovation Management, 28*(3), 327-345. doi:10.1111/j.1540-5885.2011.00801.x

Lukka, K., & Granlund, M. (1996). Cost accounting in Finland: current practice and trends of development. *European Accounting Review, 5*(1), 1-28. doi:10.1080/09638189600000001

Luo, X., Tang, J., & Kwong, C. K. (2014). A QFD-Based Optimization Method for Scalable Product Platform. In T. W. Simpson, J. Jiao, Z. Siddique, & K. Hölttä-Otto (Eds.), *Advances in Product Family and Product Platform Design: Methods & Applications* (pp. 343-365). Germany, Heidelberg: Springer.

MacCormack, A., Baldwin, C. Y., & Rusnak, J. (2012). Exploring the duality between product and organizational architectures: A test of the "mirroring" hypothesis. *Research Policy, 41*(8), 1309-1324. doi:10.1016/j.respol.2012.04.011

MacDuffie, J. P. (2013). Modularity-as-Property, Modularization-as-Process, and 'Modularity'-as-Frame: Lessons from Product Architecture Initiatives in the Global Automotive Industry. *Global Strategy Journal, 3*(1), 8-40. doi:10.1111/j.2042-5805.2012.01048.x

MacDuffie, J. P., Sethuraman, K., & Fisher, M. L. (1996). Product variety and manufacturing performance: Evidence from the International Automotive Assembly Plant Study. *Management science, 42*(3), 350-369. doi:10.1287/mnsc.42.3.350

Madni, A. M., Boehm, B., Ghanem, R. G., Erwin, D., & Wheaton, M. J. (2018). *Disciplinary Convergence in Systems Engineering Research*. Germany, Heidelberg: Springer.

Madni, A. M., & Sievers, M. (2018). Model-based systems engineering: motivation, current status, and needed advances *Disciplinary Convergence in Systems Engineering Research* (pp. 311-325): Springer.

Malmi, T. (1999). Activity-based costing diffusion across organizations: an exploratory empirical analysis of Finnish firms. *Accounting Organizations and Society, 24*(8), 649-672. doi:10.1016/S0361-3682(99)00011-2

Marion, T. J., Thevenot, H. J., & Simpson, T. W. (2007). A cost-based methodology for evaluating product platform commonality sourcing decisions with two examples. *International Journal of Production Research, 45*(22), 5285-5308. doi:10.1080/00207540600710970

Mårtensson, A., & Mårtensson, P. (2007). Extending Rigor and Relevance: Towards Credible, Contributory and Communicable Research*124*. Retrieved from https://aisel.aisnet.org/ecis2007/124

Martin, M. V., & Ishii, K. (2002). Design for variety: developing standardized and modularized product platform architectures. *Research in Engineering Design, 13*(4), 213-235. doi:10.1007/s00163-002-0020-2

Matthias, O., Fouweather, I., Gregory, I., & Vernon, A. (2017). Making sense of Big Data – can it transform operations management? *International Journal of Operations & Production Management, 37*(1), 37-55. doi:10.1108/ijopm-02-2015-0084

McKinnon, J. (1988). Reliability and Validity in Field Research: Some Strategies and Tactics. *Accounting, Auditing & Accountability Journal, 1*(1), 34-54. doi:10.1108/eum0000000004619

Merchant, K. A., & Shields, M. D. (1993). When and Why to Measure Costs Less Accuratley to Improve Decision Making. *Accounting Horizons, 7*(2), 76-81.

Mertens, K. G., Lorscheid, I., & Meyer, M. (2015). Structural Equation Modeling for Simulation Metamodeling. *Proceedings of the 2015 Winter Simulation Conference*, 701-712. doi:10.1109/WSC.2015.7408208

Mertens, K. G., Lorscheid, I., & Meyer, M. (2017). Using Structural Equation-based Metamodeling for Agent-based Models. *Proceedings of the 2017 Winter Simulation Conference*, 1372-1382. doi:10.1109/WSC.2017.8247881

Mertens, K. G., & Meyer, M. (2018). Wie schlimm sind Messfehler für die Kostenrechnung? *Controlling & Management Review, 62*(9), 28-39. doi:10.1007/s12176-018-0080-4

Meyer, M., Meßerschmidt, O., & Mertens, K. G. (2019). How much does variety-induced complexity actually cost? Linking axiomatic design with cost modeling. In M. Schröder & K. Wegener (Eds.), *Logistik im Wandel der Zeit – Von der Produktionssteuerung zu vernetzten Supply Chains - Festschrift für Wolfgang Kersten zum 60. Geburtstag* (pp. 813-827). Germany, Wiesbaden: Gabler Verlag.

Meyer, M., Zaggl, M., & Carley, K. M. (2011). Measuring CMOT's intellectual structure and its development. *Computational and Mathematical Organization Theory, 17*(1), 1-34. doi:10.1007/s10588-010-9076-0

Meyer, M. H., & Lehnerd, A. P. (1997). *The power of product platforms: building value and cost leadership*. New York, NY, USA: The Free Press.

Mikkola, J. H. (2007). Management of product architecture modularity for mass customization: Modeling and theoretical considerations. *IEEE Transactions on Engineering Management, 54*(1), 57-69. doi:10.1109/TEM.2006.889067

Mikkola, J. H., & Gassmann, O. (2003). Managing modularity of product architectures: toward an integrated theory. *IEEE Transactions on Engineering Management, 50*(2), 204-218. doi:10.1109/tem.2003.810826

Miller, J. G., & Vollmann, T. E. (1985). The hidden factory. *Harvard Business Review, 63*, 142-150.

Misra, R. B. (1975). Optimum production lot size model for a system with deteriorating inventory. *International Journal of Production Research, 13*(5), 495-505. doi:10.1080/00207547508943019

Montgomery, D. C. (2000). *Design and Analysis of Experiments* (Fifth Edition ed.). CA, Toronto: John Wiley & Sons.

Moon, S. K., & Simpson, T. W. (2014). Platform Valuation for Product Family Design. In T. W. Simpson, J. R. Jiao, Z. Siddique, & K. Höltta-Otto (Eds.), *Advances in Product Family and Product Platform Design - Methods & Applications* (Vol. 1, pp. 179-198). Germany, Heidelberg: Springer

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychol Rev, 115*(2), 502-517. doi:10.1037/0033-295X.115.2.502

Moorthy, K. S., & Png, I. P. L. (1992). Market Segmentation, Cannibalization, and the Timing of Product Introductions. *Management science, 38*(3), 345-359. doi:10.1287/mnsc.38.3.345

Morita, M., Machuca, J. A. D., & Pérez Díez de los Ríos, J. L. (2018). Integration of product development capability and supply chain capability: The driver for high performance

adaptation. *International Journal of Production Economics, 200*, 68-82. doi:10.1016/j.ijpe.2018.03.016
Mowen, M. M., Hansen, D. R., & Heitger, D. L. (2011). *Managerial Accounting: The Cornerstones of Business Decisions* (Vol. 4th International Edition). UK, Andover: Cengage Learning.
Muffatto, M. (1999). Introducing a platform strategy in product development. *International Journal of Production Economics, 60-61*, 145-153. doi:10.1016/s0925-5273(98)00173-x
Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., . . . Schwarz, N. (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. *Environmental Modelling & Software, 48*, 37-48. doi:10.1016/j.envsoft.2013.06.003
Mussa, M., & Rosen, S. (1978). Monopoly and Product Quality. *Journal of Economic Theory, 18*(2), 301-317. doi:Doi 10.1016/0022-0531(78)90085-6
Navissi, F., & Sridharan, V. G. (2017). Determinants of Target Costing Adoption: A Research Note. *Journal of Management Accounting Research, 29*(1), 67-77. doi:10.2308/jmar-51501
Negahban, A., & Smith, J. S. (2014). Simulation for manufacturing system design and operation: Literature review and analysis. *Journal of Manufacturing Systems, 33*(2), 241-261. doi:10.1016/j.jmsy.2013.12.007
Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of Information and System Quality: An Empirical Examination Within the Context of Data Warehousing. *Journal of Management Information Systems, 21*(4), 199-235. doi:10.1080/07421222.2005.11045823
Noreen, E. (1991). Conditions under which activity-based cost systems provide relevant costs. *Journal of Management Accounting Research, 3*, 159-168.
Noreen, E., & Soderstrom, N. (1994). Are overhead costs strictly proportional to activity? Evidence from hospital departments. *Journal of Accounting and Economics, 17*(1-2), 255-278. doi:10.1016/0165-4101(94)90012-4
Noreen, E., & Soderstrom, N. (1997). The accuracy of proportional cost models: Evidence from hosptical service departments. *Review of Accounting Studies, 2*, 89-114.
Oberkampf, W. L., & Roy, C. J. (2010). *Verification and validation in scientific computing*. USA, MA, Cambridge: Cambridge University Press.
Otto, K., Holtta-Otto, K., Simpson, T. W., Krause, D., Ripperda, S., & Moon, S. K. (2016). Global Views on Modular Design Research: Linking Alternative Methods to Support Modular Product Family Concept Development. *Journal of Mechanical Design, 138*(7), 16. doi:10.1115/1.4033654
Park, J., & Simpson, T. W. (2005). Development of a production cost estimation framework to support product family design. *International Journal of Production Research, 43*(4), 731-772. doi:10.1080/00207540512331311903
Park, J., & Simpson, T. W. (2008). Toward an activity-based costing system for product families and product platforms in the early stages of development. *International Journal of Production Research, 46*(1), 99-130. doi:10.1080/00207540600825240
Pasche, M., Persson, M., & Löfsten, H. (2011). Effects of platforms on new product development projects. *International Journal of Operations & Production Management, 31*(11), 1144-1163. doi:10.1108/01443571111178475
Pearl, J. (2009). *Causality: models, reasoning, and inference* (Vol. 2). USA, MA, Cambridge: Cambridge University Press.

Pietzsch, B., Fiedler, S., Mertens, K. G., Richter, M., Scherer, C., eacute, . . . Berger, U. (2020). Metamodels for Evaluating, Calibrating and Applying Agent-Based Models: A Review. *Journal of Artificial Societies and Social Simulation, 23*(2), 9. doi:10.18564/jasss.4274

Pine, B. J., Bart, V., & Boynton, A. C. (1993). Making mass customization work. *Harward Business Review, 71*(5), 108-110.

Polhill, J. G., Filatova, T., Schlüter, M., & Voinov, A. (2016). Modelling systemic change in coupled socio-environmental systems. *Environmental Modelling & Software, 75*, 318-332. doi:10.1016/j.envsoft.2015.10.017

Popper, K. (1998). *Logik der Forschung*. Germany, Berlin: Akademie Verlag.

Porter, M. E. (1985a). *Competitive advantage: creating and sustaining superior performance*. USA, NY, New York: The Free Press.

Porter, M. E. (1985b). Technology and Competitive Advantage. *Journal of Business Strategy, 5*(3), 60-78. doi:10.1108/eb039075

Puente León, F. (2015). *Messtechnik - Systemtheorie für Ingenieure und Informatiker* (Vol. 10). Germany, Berlin: Springer.

Quattrone, P. (2016). Management accounting goes digital: Will the move make it wiser? *Management Accounting Research, 31*, 118-122. doi:10.1016/j.mar.2016.01.003

Raasch, C., Lee, V., Spaeth, S., & Herstatt, C. (2013). The rise and fall of interdisciplinary research: The case of open source innovation. *Research Policy, 42*(5), 1138-1151. doi:10.1016/j.respol.2013.01.010

Raghavan Srinivasan, S., Ramakrishnan, S., & Grasman, S. E. (2005). Identifying the effects of cannibalization on the product portfolio. *Marketing Intelligence & Planning, 23*(4), 359-371. doi:10.1108/02634500510603465

Ramdas, K. (2003). Managing Product Variety: An Integrative review and research directions. *Production and Operations Management, 12*(1), 79-101. doi:1059-1478/03/1201/079$1.25

Ramos, A. L., Ferreira, J. V., & Barceló, J. (2012). Model-based systems engineering: An emerging approach for modern systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 42*(1), 101-111. doi:10.1109/TSMCC.2011.2106495

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing, 28*(3), 181-193. doi:10.1016/j.ijresmar.2011.04.002

Rathnow, P. J. (1993). *Intergriertes Variantenmanagement: Bestimmung, Realisierung und Sicherung der Optimalen Produktvielfalt*. Germany, Göttingen: Vandenhoeck & Ruprecht.

Ravasi, D., & Stigliani, I. (2012). Product Design: a Review and Research Agenda for Management Studies. *International Journal of Management Reviews, 14*(4), 464-488. doi:10.1111/j.1468-2370.2012.00330.x

Riley, D. (1987). Competitive cost based investment stragies for industrial companies *Manufacturing Issues*. USA, NY, New York: Booz Allen & Hamilton.

Ripperda, S. (2019). *Methodische Unterstützung zur kostenbasierten Auswahl modularer Produktstrukturen*. Germany, Hamburg: Springer.

Ripperda, S., & Krause, D. (2017). Cost Effects of Modular Product Family Structures: Methods and Quantification of Impacts to Support Decision Making. *Journal of Mechanical Design, 139*(2). doi:10.1115/1.4035430

Robertson, D., & Ulrich, K. (1998). Planning for Product Platforms. *Sloan management review, 39*(4), 19-31.

Robinson, S. (2008a). Conceptual modelling for simulation Part I: definition and requirements. *Journal of the Operational Research Society, 59*(3), 278-290. doi:10.1057/palgrave.jors.2602368

Robinson, S. (2008b). Conceptual modelling for simulation Part II: a framework for conceptual modelling. *Journal of the Operational Research Society, 59*(3), 291-304. doi:10.1057/palgrave.jors.2602369

Rosen, S. L., & Guharay, S. K. (2013). A Case Study Examining the Impact of Factor Screening for Neural Network Metamodels. In R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, & M. E. Kuhl (Eds.), *Proceedings of the 2013 Winter Simulation Conference* (pp. 486-496). USA, NJ, Piscataway: IEEE.

Rosenberg, O. (2002). Kostensenkung durch Komplexitätsmanagement. In K.-P. Franz & P. Kajüter (Eds.), *Kostenmanagement - Wertsteigerung durch systematische Kostensteuerung*. Germany, Stuttgart: Schäffer Poeschel.

Rumelhart, D. E., McClelland, J. L., & Group, P. R. (1987). *Parallel Distributed Processing:Explorations in the Microstructure of Cognition: Foundations*. USA, MA, Cambridge: MIT Press.

Salvador, F. (2007). Toward a Product System Modularity Construct: Literature Review and Reconceptualization. *IEEE Transactions on Engineering Management, 54*(2), 219-240. doi:10.1109/tem.2007.893996

Salvador, F., Forza, C., & Rungtusanatham, M. (2002). Modularity, product variety, production volume, and component sourcing: theorizing beyond generic prescriptions. *Journal of Operations Management, 20*(5), 549-575. doi:10.1016/S0272-6963(02)00027-X

Sanchez, R., & Mahoney, J. T. (1996). Modularity, flexibility, and knowledge management in product and organization design. *Strategic Management Journal, 17*(S2), 63-76. doi:10.1002/smj.4250171107

Sanchez, S. M., & Lucas, T. W. (2002). Exploring the world of Agent-Based Simulations: Simple Models, Complex Analysis. In E. Yücesan, C.-H. Chen, J. L. Snwodon, & C. J. M. (Eds.), *Proceedings of the 2002 Winter Simulation Conference* (pp. 116-126). USA, NJ, Piscataway: IEEE.

Sargent, R. G. (1991). Research Issues in Metamodeling. In B. L. Nelson, W. D. Kelton, & G. M. Clark (Eds.), *Proceedings of the 1991 Winter Simulation Conference*. USA, NJ, Piscataway: IEEE.

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation, 7*(1), 12-24. doi:10.1057/jos.2012.20

Schilling, M. A. (2000). Toward a General Modular Systems Theory and Its Application to Interfirm Product Modularity. *Academy of Management Review, 25*(2), 312-334. doi:10.5465/amr.2000.3312918

Schilling, M. A., & Steensma, H. K. (2001). The use of modular organizational forms: An industry-level analysis. *Academy of Management Journal, 44*(6), 1149-1168. doi:10.2307/3069394

Schmenner, D. (1986). How Can Service Business Survive and Prosper? *Sloan management review, 27*(3), 21-32.

Schoute, M. (2009). The relationship between cost system complexity, purposes of use, and cost system effectiveness. *The British Accounting Review, 41*(4), 208-226. doi:10.1016/j.bar.2009.10.001

Schoute, M. (2011). The relationship between product diversity, usage of advanced manufacturing technologies and activity-based costing adoption. *The British Accounting Review, 43*(2), 120-134. doi:10.1016/j.bar.2011.02.002

Schuh, G. (1989). *Gestaltung und Bewertung von Produktvarianten* (Vol. 177). Germany, Düsseldorf: VDI-Verlag GmbH.

Schuh, G. (2005). *Produktkomplexität managen: Strategien - Methoden - Tools* (Vol. 2). Germany, München: Hanser.

Schuh, G., Riesener, M., Breunig, S., Koch, J., & Kuntz, J. (2017). Evaluation of Variety-induced Costs in Product-Service Systems (PSS). *Procedia CIRP, 61*, 673-678. doi:10.1016/j.procir.2016.11.239

Schulze, J., Müller, B., Groeneveld, J., & Grimm, V. (2017). Agent-based Modelling of Social-Ecological Systems: Achievements, Challenges, and a Way Forward. *Journal of Artificial Societies and Social Simulation, 20 (2)*(8). doi:10.18564/jasss.3423

Shank, J. K., & Govindarajan, V. (1988). The Perils of Cost Allocation Based on Production Volumes. *Accounting Horizons, 2*(4), 71-79.

Shank, J. K., & Govindarajan, V. (1989). *Strategic Cost Analysis - The Evolution from Managerial to Strategic Accounting*. USA, NY, New York: The Free Press.

Shank, J. K., & Govindarajan, V. (1993). *Strategic Cost Management - A New Tool for Competitive Advantage* USA, NY, New York: The Free Press.

Shannon, R. E. (1975). *Systems simulation; the art and science*. USA, NY, New York: Prentice Hall.

Sharman, D. M., & Yassine, A. A. (2004). Characterizing complex product architectures. *Systems Engineering, 7*(1), 35-60. doi:10.1002/sys.10056

Shepard, R. W. (2015). *Theory of Cost and Production Functions*. UK, Oxfordshire: Princeton University Press.

Shmueli, G. (2010). To Explain or to Predict? *Statistical Science, 25*(3), 289-310. doi:10.1214/10-Sts330

Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly, 35*(3), 553-572. doi:10.2307/23042796

Siddique, Z., & Repphun, B. (2001). Estimating cost savings when implementing a product platform approach. *Concurrent Engineering-Research and Applications, 9*(4), 285-294. doi:10.1177/1063293X0100900405

Siebers, P. O., Macal, C. M., Garnett, J., Buxton, D., & Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation, 4*(3), 204-210. doi:10.1057/jos.2010.14

Siebertz, K., van Bebber, D., & Hochkirchen, T. (2010). *Statistische Versuchsplanung - Design of Experiments (DoE)* (Vol. 1). Germany, Heidelberg: Springer.

Simon, H. A. (1962). The Architecture of Complexity. *Proceedings of the American Philosophical Society, 106*(6), 467-482.

Simpson, T. W. (2004). Product platform design and customization: Status and promise. *Artificial Intelligence for Engineering Design, analysis and Manufacturing 18*(1), 3-20. doi:10.10170S0890060404040028

Simpson, T. W., Bobuk, A., Slingerland, L. A., Brennan, S., Logan, D., & Reichard, K. (2011). From user requirements to commonality specifications: an integrated approach to product family design. *Research in Engineering Design, 23*(2), 141-153. doi:10.1007/s00163-011-0119-4

Simpson, T. W., Jiao, J., Siddique, Z., & Hölttä-Otto, K. (2014). *Advances in Product Family and Product Platform Design*. USA, NY, New York: Springer.

Simpson, T. W., Maier, J. R., & Mistree, F. (2001). Product platform design: method and application. *Research in Engineering Design, 13*(1), 2-22. doi:10.1007/s001630100002

Skirde, H., Kersten, W., & Schröder, M. (2016). Measuring the Cost Effects of Modular Product Architectures — A Conceptual Approach. *International Journal of Innovation and Technology Management, 13*(04), 1650017. doi:10.1142/s0219877016500176

Slovic, P., & Lichtenstein, S. (1971). Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational behavior and human performance, 6*(6), 649-744. doi:10.1016/0030-5073(71)90033-x

Smith, E. B., & Rand, W. (2018). Simulating Macro-Level Effects from Micro-Level Observations. *Management science, 64*(11), 5405-5421. doi:10.1287/mnsc.2017.2877

Sosa, M. E., Eppinger, S. D., & Rowles, C. M. (2003). Identifying Modular and Integrative Systems and Their Impact on Design Team Interactions. *Journal of Mechanical Design, 125*(2), 240. doi:10.1115/1.1564074

Sosa, M. E., Eppinger, S. D., & Rowles, C. M. (2004). The Misalignment of Product Architecture and Organizational Structure in Complex Product Development. *Management science, 50*(12), 1674-1689. doi:10.1287/mnsc.1040.0289

Squazzoni, F. (2012). *Agent-Based Computational Sociology*. USA, NY, New York: John Wiley & Sons.

Starr, M. K. (2010). Modular production – a 45-year-old concept. *International Journal of Operations & Production Management, 30*(1), 7-19. doi:10.1108/01443571011012352

Stein, M., Beer, M., & Kreinovich, V. (2013). Bayesian Approach for Inconsistent Information. *Information sciences, 245*, 96-111. doi:10.1016/j.ins.2013.02.024

Stergioulas, N. (2009). Numerical Simulations of Black Hole Formation. In E. Papantonopoulos (Ed.), *Physics of Black Holes: A Guided Tour* (pp. 177-208). Germany, Berlin: Springer.

Stone, R. B., & Wood, K. L. (2000). Development of a functional basis for design. *Journal of Mechanical Design, 122*(4), 359-370. doi:10.1115/1.1289637

Suh, N. P. (1995). Axiomatic Design of Mechanical Systems. *Journal of Mechanical Design, 117*, 2-10. doi:10.1115/1.2836467

Suh, N. P. (1998). Axiomatic Design Theory for Systems. *Research in Engineering Design, 10*(4), 189-209. doi:10.1007/s001639870001

Suh, N. P. (2001). *Axiomatic Design. Advances and Applications.* USA, NY, New York: Oxford University Press.

Suh, N. P. (2005). *Complexity: Theory and Application*. USA, NY, New York: Oxford University Press.

Tang, J., Y.K. Fung, R., Xu, B., & Wang, D. (2002). A new approach to quality function deployment planning with financial consideration. *Computers & Operations Research, 29*(11), 1447-1463. doi:10.1016/s0305-0548(01)00041-7

Thiele, J. C., & Grimm, V. (2015). Replicating and breaking models: good for you and good for ecology. *Oikos, 124*(6), 691-696. doi:10.1111/oik.02170

Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating Parameter Estimation and Sensitivity Analysis of Agent-Based Models: A Cookbook Using NetLogo and 'R'. *Journal of Artificial Societies and Social Simulation, 17*(3). doi:10.18564/jasss.2503

Thielman, J., & Ge, P. (2006). Applying axiomatic design theory to the evaluation and optimization of large-scale engineering systems. *Journal of Engineering Design, 17*(1), 1-16. doi:10.1080/09544820500287722

Thonemann, U. W., & Brandeau, M. L. (2000). Optimal Commonality in Component Design. *Operations Research, 48*(1), 1-19. doi:10.1287/opre.48.1.1.12445

Thyssen, J., Israelsen, P., & Jørgensen, B. (2006). Activity-based costing as a method for assessing the economics of modularization—A case study and beyond. *International Journal of Production Economics, 103*(1), 252-270. doi:10.1016/j.ijpe.2005.07.004

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management, 14*(3), 207-222. doi:10.1111/1467-8551.00375

Trattner, A., Hvam, L., Forza, C., & Herbert-Hansen, Z. N. L. (2019). Product complexity and operational performance: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology, 25*, 69-83. doi:10.1016/j.cirpj.2019.02.001

Treleven, M., & Wacker, J. G. (1987). The sources, measurements, and managerial implications of process commonality. *Journal of Operations Management, 7*(1-2), 11-25. doi:10.1016/0272-6963(87)90003-9

Tseng, M. M., & Jiao, J. (1997). A module identification approach to the electrical design of electronic products by clustering analysis of the design matrix. *Computers & Industrial Engineering, 33*(1), 229-233. doi:10.1016/S0360-8352(97)00081-8

Ulrich, K. (1995). The role of product architecture in the manufacturing firm. *Research Policy, 24*(3), 419-440. doi:10.1016/0048-7333(94)00775-3

Ulrich, K., & Ellison, D. J. (1999). Holistic Customer Requirements and the Design-Select Decision. *Management science, 45*(5), 641-658. doi:10.1287/mnsc.45.5.641

Ulrich, K., & Eppinger, S. D. (2012). *Product design and development* (Vol. 5th ed.). New York, NY, USA: McGraw-Hill.

Van den Broeke, M., Boute, R., & Samii, B. (2015). Evaluation of product-platform decisions based on total supply chain costs. *International Journal of Production Research, 53*(18), 5545-5563. doi:10.1080/00207543.2015.1034329

Van den Steen, E. (2011). Overconfidence by Bayesian-Rational Agents. *Management science, 57*(5), 884-896. doi:10.1287/mnsc.1110.1323

Van der Auweraer, H., Anthonis, J., De Bruyne, S., & Leuridan, J. (2012). Virtual engineering at work: the challenges for designing mechatronic products. *Engineering with Computers, 29*(3), 389-408. doi:10.1007/s00366-012-0286-6

Van Gigch, J. P. (1991). *System design modeling and metamodeling*. USA, NY, Spring Street: Plenum, Press.

Vickery, S. K., Koufteros, X., Dröge, C., & Calantone, R. (2016). Product Modularity, Process Modularity, and New Product Introduction Performance: Does Complexity Matter? *Production and Operations Management, 25*(4), 751-770. doi:10.1111/poms.12495

Vogelsberger, M., Genel, S., Springel, V., Torrey, P., Sijacki, D., Xu, D., . . . Hernquist, L. (2014). Properties of galaxies reproduced by a hydrodynamic simulation. *Nature, 509*(7499), 177-182. doi:10.1038/nature13316

Voss, C. A., & Hsuan, J. (2009). Service Architecture and Modularity. *Decision Sciences, 40*(3), 541-569. doi:10.1111/j.1540-5915.2009.00241.x

Waldherr, A., & Wijermans, N. (2013). Communicating Social Simulation Models to Sceptical Minds. *Journal of Artificial Societies and Social Simulation, 16*(4). doi:10.18564/jasss.2247

Watanabe, C., & Ane, B. K. (2004). Constructing a virtuous cycle of manufacturing agility: concurrent roles of modularity in improving agility and reducing lead time. *Technovation, 24*(7), 573-583. doi:10.1016/S0166-4972(02)00118-9

Weber, J. (2005). *Gestaltung der Kostenrechnung - Notwendigkeit, Optionen und Konsequenzen* (Vol. 21). Germany, Wiesbaden: Deutscher Universitäts-Verlag.

Weiss, D. (2010). Cost Behavior and Analysts' Earnings Forecasts. *The Accounting Review, 85*(4), 1441-1471. doi:10.2308/accr.2010.85.4.1441

Weiss, G. (Ed.) (2000). *Multiagent Systems - A Modern Approach to Distributed Modern Approach to Artificial Intelligence*. USA, MA, Cambridge: The MIT Press.

Werner, B. T., & McNamara, D. E. (2007). Dynamics of coupled human-landscape systems. *Geomorphology, 91*(3-4), 393-407. doi:10.1016/j.geomorph.2007.04.020

Williamson, O. E. (1979). Transaction-cost economics: the governance of contractual relations. *The journal of Law and Economics, 22*(2), 233-261.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American journal of sociology, 87*(3), 548-577.
Wilson, S., & Perumal, A. (2009). *Waging war on complexity costs*. USA, NY, New York: McGraw-Hill
Wouters, M., & Morales, S. (2014). The Contemporary Art of Cost Management Methods during Product Development. *Advances in Management Accounting, 24*, 259-346. doi:10.1108/S1474-787120140000024008
Wouters, M., Morales, S., Grollmuss, S., & Scheer, M. (2016). Methods for Cost Management during Product Development: A Review and Comparison of Different Literatures. *Advances in Management Accounting, 26*, 139-274. doi:10.1108/S1474-787120150000026005
Wouters, M., & Stadtherr, F. (2018). Cost management and modular product design strategies. In E. Harris (Ed.), *Routledge Companion to Performance Management & Control* (pp. 54-86). UK, London: Routledge.
Xiong, Y., Du, G., & Jiao, J. (2018). Modular product platforming with supply chain postponement decisions by leader-follower interactive optimization. *International Journal of Production Economics, 205*, 272-286. doi:10.1016/j.ijpe.2018.09.013
Xu, Q., & Jiao, J. (2014). Managing Design Processes of Product Families by Modularization and Simulation. In T. W. Simpson, J. Jiao, Z. Siddique, & K. Hölttä-Otto (Eds.), *Advances in Product Family and Product Platform Design*. USA, NY, New York: Springer.
Xu, Q., Jiao, J., Yang, X., Helander, M., Khalid, H. M., & Opperud, A. (2009). An analytical Kano model for customer need analysis. *Design Studies, 30*(1), 87-110. doi:10.1016/j.destud.2008.07.001
Yan, T., & Wagner, S. M. (2017). Do what and with whom? Value creation and appropriation in inter-organizational new product development projects. *International Journal of Production Economics, 191*, 1-14. doi:10.1016/j.ijpe.2017.05.010
Yassine, A., Whitney, D., Daleiden, S., & Lavine, J. (2003). Connectivity maps: modeling and analysing relationships in product development processes. *Journal of Engineering Design, 14*(3), 377-394. doi:10.1080/0954482031000091103
Zellner, A. (2002). Information processing and Bayesian analysis. *Journal of Econometrics, 107*(1-2), 41-50. doi:10.1016/S0304-4076(01)00112-9
Zengin, Y., & Ada, E. (2010). Cost management through product design: target costing approach. *International Journal of Production Research, 48*(19), 5593-5611. doi:10.1080/00207540903130876
Zimmerman, J. L. (1979). The Costs and Benefits of Cost Allocations. *The Accounting Review, 1*(July), 504-521.

10. Appendix

10.1 Detailed algorithms for the simple single cost drivers

Heuristic	Formal model description of the cost driver heuristic for overhead allocation
Production volume (DIV)	Using realized demand q from a product n and calculating the relative weights. This provides the allocation base ($q_n/\Sigma(q_n)$)
Direct labor[56] (DLH)	Calculating products' *average estimate* AV_n of all consumed unit-level activity measures (AVs_{UNIT}). Then, using each relative weight in the context of the total sum, which provides the respective allocation base ($AV_n/\Sigma(AV_n)$)
Volume-based predetermined overhead calculation (UAM)	Using the activity measures AV from the largest unit-level activity AV_{UNIT} in terms of costs (i.e., large machines) as the allocation base for all products n ($AV_n/\Sigma(AV_n)$)
Non-unit-based predetermined overhead calculation (NUAM)	Using the activity measures AVs from the largest non-unit-level activity $AV_{NON\text{-}UNIT}$ in terms of costs (i.e., largest setup process) as an allocation base (AV_n /$\Sigma(AV_n)$)
Direct material input requirements (DM)	Using a uniformly drawn material requirement M in accordance with Christensen and Demski (1997). Then, calculating the relative product weights ($M_n/\Sigma(M_n)$) to build the cost allocation base.

[56] This heuristic parallels the "average" heuristic of Balakrishnan et al. (2011) but solely incorporates individual unit-level activity measures such as direct labor hours and direct machine hours. Importantly, this cost driver has more information efforts, but is still applicable in firm settings.

10.2 Numerical example I

Numerical example in accordance with Horngren et al. (2014)

DIRECT COSTS [$]

	Simple lenses (SL)	**Complex** lenses (CL)
Labor	600,000	195,000
Manufacturing	1,125,000	675,000
Mold cleaning	120,000	150,000
Sum of direct costs	**1,845,000**	**2,865,000**
Direct costs per unit	**30.75**	**68**

INDIRECT COSTS [$]

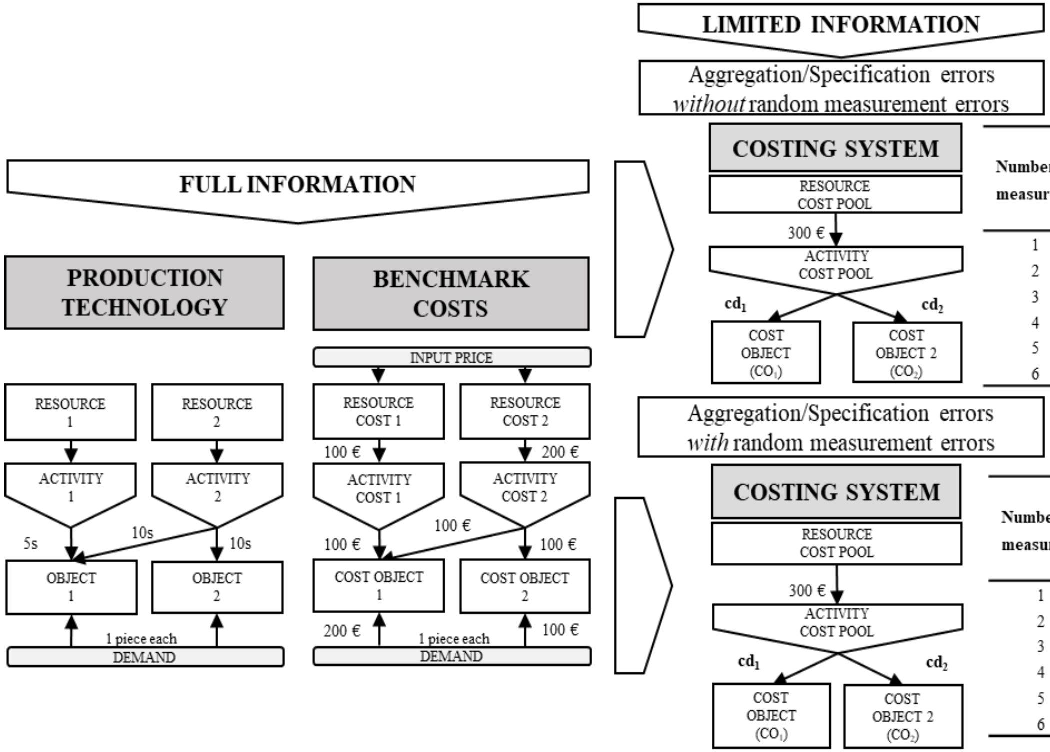
Activities	**Cost category**	**Activity measures**		**Overheads**	
		SL	**CL**	SL	CL
Design	Product-sustaining	30	70	135,000	315,000
Setup	Batch-level	500	1,500	75,000	225,000
Machine operations	Unit-level	9,000	3,750	450,000	187,500
Shipments	Batch-level	100	100	40,500	40,500
Distribution	Unit-level	45,000	22,500	261,000	130,500
Administration	Facility-sustaining[1]	30,000	9,750	192,453	130,500
		TOTAL		**1,153,953**	**961,047**
		ABC		**19.23**	**64.07**
		TC		**30**	**39**

PRODUCT COST CALCULATION [$]

	Benchmark costing system	**Heuristic costing system**	**Percentage error [PE%]**
SL 60.000 lenses	**49.98**	**60.75**	**21.54%**
CL 15.000 lenses	**132.07**	**107**	**-18.98%**

1 Facility-sustaining activities are related to administrative activities, which are completely random in modeling following Noreen (1991),

10.3 Numerical example II



Number of measures	Activity measures cd		Cost objects CO		Cost measurement error	
	cd_1	cd_2	CO_1	CO_2	$Error_1$	$Error_2$
1	10s	10s	150€	150€	-25%	50%
2	10s	10s	150€	150€	-25%	50%
3	10s	10s	150€	150€	-25%	50%
4	10s	10s	150€	150€	-25%	50%
5	10s	10s	150€	150€	-25%	50%
6	10s	10s	150€	150€	-25%	50%

	CO_1	CO_2
Bias	-25%	50%
Imprecision	0	0

Number of measures	Activity measures		Cost objects		Cost measurement error	
	cd_1	cd_2	CO_1	CO_2	$Error_1$	$Error_2$
1	7,5s	12.5s	112.5€	187.5€	-43.75%	87.50%
2	15s	5s	225€	75€	12.50%	-25.50%
3	12.5s	7.5s	187.5€	112.5€	-6.25%	12.50%
4	5s	15s	75€	225€	-62.25%	125%
5	8s	12s	120€	180€	-40%	80%
6	4s	16s	60€	240€	-70%	140%

	CO_1	CO_2
Bias	-25%	50%
Imprecision	58.60%	117.63%

Based on a fixed scenario with benchmark costs, the example illustrates various circumstances of costing systems with respect to *bias* and *imprecision*. The first costing system (see the upper costing system) includes random measurement errors but incorporates aggregation and specification errors. Hence, among the number of measures, costly errors for both product costs remain constant (-25%, 50%). This constant systematic drift reflects *bias*. The second costing system (see the lower one) accounts for random measurement errors. Interestingly, measures are dispersing and seemingly uncontrollable. At this point, both product costs are due to imprecision (58.60%, 117.63%). Accordingly, this figure depicts the setting that even varying cost measures can be due to unreasonable deviations in resource consumption. Our experimental design in the study follows this mechanism in many circumstances.

10.4 Bayesian updating for conjugate priors (normal distribution)

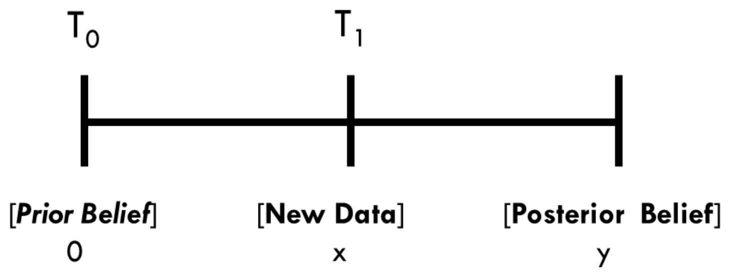
This subsection demonstrates the numerical calculation of Bayesian updating assuming conjugate priors under a framework of normal distributions.

Imagine that one has a prior belief at T_0 consisting of μ_0 and σ_0. Then, there is new data *x* at T_1 with *n* observations consisting of μ_x and σ_x.

$$x \mid \mu_0 \sim Normal\ distribution$$

$$\mu_0 \sim Normal\ distribution$$

The data updates the existing prior belief *0* and end in the new posterior belief of *y* consisting of μ_y and σ_y. The updating procedure is shown in the Figure below.



Mean calculation of the posterior:

$$\mu_y = \left(\frac{\mu_0}{\sigma_0^2} + \frac{\mu_x}{\sigma_1^2/n}\right)$$

Variance-centered mean calculation of the posterior:

$$\mu_y = \mu_0 + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_x^2}(\mu_x - \mu_0)$$

Variance calculation of the posterior:

$$\sigma_y^2 = \left(\frac{1}{\sigma_0^2} + \frac{1}{\sigma_x^2/n}\right)^{-1}$$

10.5 Experimental designs

Table 25: Experimental design – Horizontal leveraging

Independent parameters		Control parameters		Dependent parameter
OD	[Low, Mid, High]	Processes	20	Total cost difference [%]
Q_VAR	[-2,-1,0,1,2]	Resources	20	
AV_DENS	[0.35,0.5,0.85]	Products/Customers	9	
PA_DENS	[0,0.2,0.4,0.8,1]	Repetitions	50	
UNIT_SHARE	[0.3,0.5,0.7]	Total costs	1,000€	
RC_VAR	[0.5,RND,2]	Total demand	100	
NUMB_CM	[9,18,27]			
n=121,500 ($3^4 \cdot 5 \cdot 6 \cdot 50$)				

Table 26: Experimental design – Persistency of bias and imprecision

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,RND,0.85]	Products	50	APE [%]
Q_VAR	[0.5,RND,1.5]	Processes	50	Bias [%]
RC_VAR	[0.4,RND,0.7]	Resources	50	Imprecision [%]
UNIT_SHARE	[0.4,RND,0.7]	Repetitions	150	
COR	0	Total costs	1,000,000€	
ERROR	[0.1,0.3,0.5]	ABC(CPH)	Correl-Size	
CP	[1:10:50]	ABC(CDH)	Big pool	
n=135,000 ($6 \cdot 3 \cdot 150 \cdot 50$)				

Table 27: Experimental design – TVC system with departments and unit-level cost drivers

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,0.6,0.85]	Products	50	Euclidean distance [EUCD€]
Q_VAR	[0.5,1,1.5]	Processes	50	
RC_VAR	[0.4,RND,0.7]	Resources	50	
UNIT_SHARE	[0.3,0.5,0.7]	Repetitions	20	
COR	[-0.6,0,0.6]	Total costs	1,000,000€	
ERROR	0	**TVC(CPH)**	**UnitSizeRandom**	
CP	**[1,2,...,10,12,15]**	**TVC(CDH)**	**UAM**	
N=12,960 ($3^4 \cdot 20 \cdot 8$)				

Table 28: Experimental design – Bayesian updating

Independent parameters		Control parameters		Dependent parameters
DENS	0.6	Products	50	Bias [%]
Q_VAR	1	Processes	50	Imprecision [%]
RC_VAR	0.55	Resources	50	
UNIT_SHARE	0.5	Repetitions	40	
COR	0	Total costs	1,000,000€	
ERROR	**[0.1,0.3,0.5]**	ABC(CPH)	Correl-Size	
CP	10	ABC(CDH)	Big pool	
PERIOD	**12**			

n=72,000 (3 · 12 · 40 · 50)

Table 29: Experimental design – Pricing experiment

Independent parameters		Control parameters		Dependent parameters
DENS	[0.35,RND,0.85]	Products	50	Δ Profit [%]
Q_VAR	[0.5,RND,1.5]	Processes	50	
RC_VAR	[0.4,RND,0.7]	Resources	50	
UNIT_SHARE	[0.4,RND,0.7]	Repetitions	20	
COR	0	α	200	
ERROR	**0.1,0.3,0.5**	β	15	
CP	10	Total costs	1,000,000€	
PERIOD	**100**	ABC(CPH)	Correl-Size	
		ABC(CDH)	Big pool	

n=6,000 (3 ·100 ·20); The experiment of imprecision focuses on a 10 resource environment. Then, a small costing system can completely outweigh the bias.