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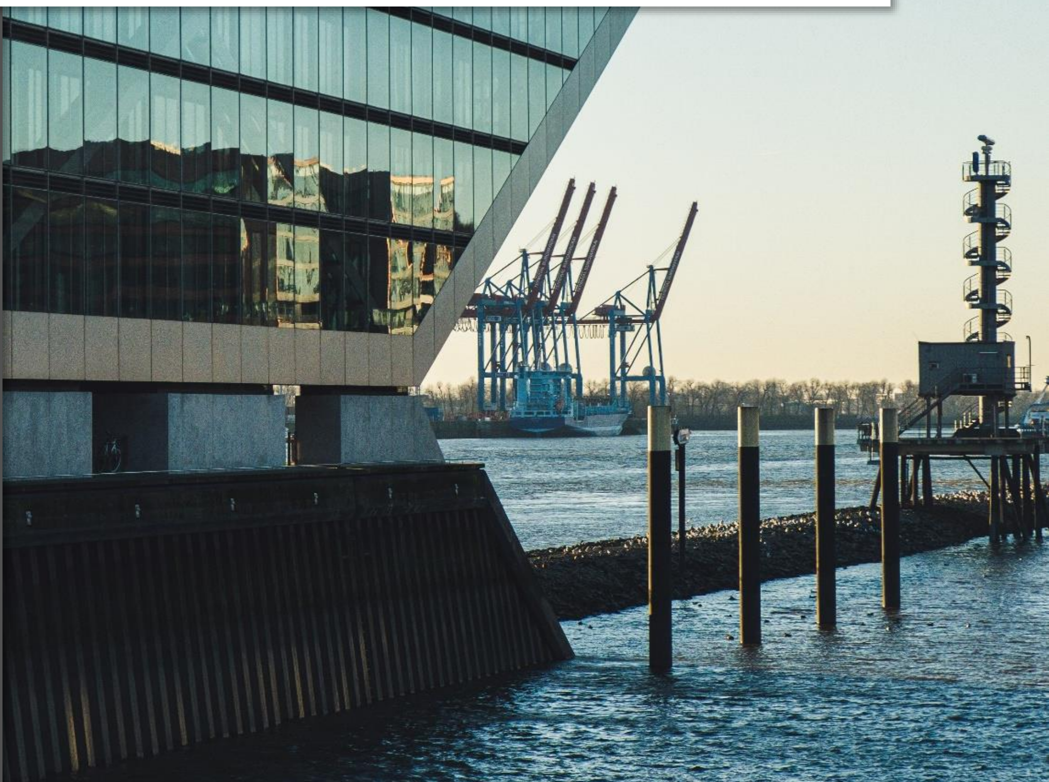

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Efficiency measurement of grocery retail warehouses with DEA

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Purpose: *To enable reliable food supply and to remain competitive, grocery retailers need to operate efficient distribution networks. Therefore, the purpose of this paper is to develop and apply a multi-criteria evaluation framework considering the complexity of grocery retail warehouses while maintaining the highest possible efficiency.*

Methodology: *We propose data envelopment analysis (DEA) as a non-parametric method of efficiency measurement and use an empirical seven-year dataset of 12 grocery retail warehouses. Four inputs and six outputs are included. We examine the efficiency development with DEA window analysis for longitudinal efficiency evaluation. By adding super efficiency, the model gains discriminatory power for efficient warehouses. We provide concrete improvement targets for all non-efficient warehouses through slack-based measurement.*

Findings: *As a method for multi-criteria efficiency evaluation, DEA models provide interesting results for efficiency measurement in food supply chains. Through the non-parametric multi-criteria approach, it enables an objective and holistic analysis perspective. By choosing inputs and outputs independently of their measurement unit, flexible application possibilities appear, giving non-monetary elements the necessary importance in optimization.*

Originality: *Although there are several studies dealing with the efficiency measurement of warehouses using DEA, our approach is the first to explore its application in food retail warehouse logistics over several periods.*

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1 Introduction

Warehouses play a decisive role in every retail supply chain. Their main tasks are to receive and store items from industry partners for subsequent order picking, as well as shipment to the customers (Richards, 2018). In stationary grocery retailing, also referred to as brick-and-mortar grocery retailing (Wollenburg, et al., 2018), these customers are grocery stores ordering items in regular order-delivery cycles manually or automated. In this study, we focus on warehouses processing high-volume-low-mix orders which are typical for distribution centers serving brick-and-mortar grocery structures (Boysen, Koster and Füßler, 2021). Within these warehouses, cooled and non-cooled perishable items, as well as non-perishable items, are processed and delivered on fixed delivery days known in advance (Hübner, Wollenburg and Holzapfel, 2016). Because the competition levels in retail are generally considered to be high in the grocery section, especially in the oligopolistic Germany retailing segment, empirical efficiency measurement methods are in high demand as a basis for informed management decisions in the sector. As in many cases, the details of such an endeavor are not so perfectly clear as theory might suggest. The theoretical knowledge is therefore of relevance in this area in order to be able to make objective decisions and to gain advantages in the competition for displacement. In this context, the classical controlling approaches to multi-criteria evaluation always provide a strong subjectivity due to strong human influences of the weighting. A comparison by Chlupsa from 2017 illustrates the explosive nature of this situation (Chlupsa, 2017). He questions whether management, whose private decisions are emotionally influenced, can meet the strict rational requirements when it comes to professional decisions. What is needed, therefore, is an instrument that helps management to be able to make decisions in whose alternatives, on the one hand, all important factors are taken into account and, on the other hand, no subjective weighting of these factors is necessary.

We aspire to answer the following research questions: (1) What are the components of an efficiency analysis aiming to evaluate the performance of warehouses in brick-and-mortar retailing, and (2) what are the main potentials for the examined warehouses when aspiring to increase their performance? Therefore, we formulate and conduct a longterm non-parametric Data Envelopment Analysis (DEA) model for seven historical years and with ten input and output types for the efficiency of grocery retailing is, therefore, an interesting objective of this research.

The use of Data Envelopment Analysis (DEA), as a multi-criteria, non-parametric method for measuring efficiency, is intended to help answer the question of the efficiency of distribution centers within a homogeneous logistics landscape. Previous approaches in classical logistics controlling can be differentiated from the DEA method with regard to the different methods of efficiency measurement. As a non-parametric method, DEA represents a completely different approach. DEA as a method with a model-generic weighting of input and output factors contributes to an objective benchmark. In addition, DEA always provides a relative efficiency of the investigated units. This means that for each unit under investigation, it can be determined whether it can be counted among the efficient units or how much it is below them.

In order to motivate and legitimate the application of this specific method, a method analysis is first conducted in Section 2. In addition, Section 3 presents the basic characteristics and extensions of the DEA method family. Section 4 provides the model formulation and results, and Section 5 outlines discussion points for retail and warehouse management.

2 Theoretical Background

2.1 Efficiency measurement methods

The permanent development within the logistics systems also requires a continuous drive for optimization of the participants of these systems. Since not all market participants are pioneers within the supply chain or are able to do so. In many places, an orientation towards the best-practice solution offers itself. The instrument of benchmarking is one variant through which this best practice solution can be found (Berens, 1997). Figure 1 provides an overview of the various methods for measuring efficiency (Hammerschmidt, 2006). The classification is basically made into first- and second-generation processes. The first-generation methods can be divided into classes

I-III. Class I methods are purely output-related key indicators. These include, for example, sales, packages, or transport units. Class II key indicators are exclusively input-related, for example, personnel costs or the number of orders. In the case of class III key indicators, the input- and output-related factors of classes I and II are set in relation to each other. This results, for example, in key indicators such as personnel costs per package. To evaluate efficiency, these absolute or relative key indicators of the decision-making units under consideration can be compared with each other in the form of a ranking. As a result of the single-input/single-output case, it is not possible to make an overall statement about the efficiency of the decision-making units under consideration. The change of the considered ratio can completely dissolve the consistency of the benchmark. The second block consists of 2nd generation methods. These are not simple ratios but production functions that establish a mathematical relationship between input and output. In addition, all relevant inputs and outputs are considered simultaneously. The production function makes it possible to determine a technology set and, as a result, to make a statement about the overall efficiency of a decision unit under consideration. Basically, two methods can be classified. Class IV contains the parametric methods. In these methods, the weights of the individual inputs and outputs are defined a priori. Class V contains the non-parametric methods. In this method, the weighting is carried out model-endogenously by the model itself during the efficiency calculation.

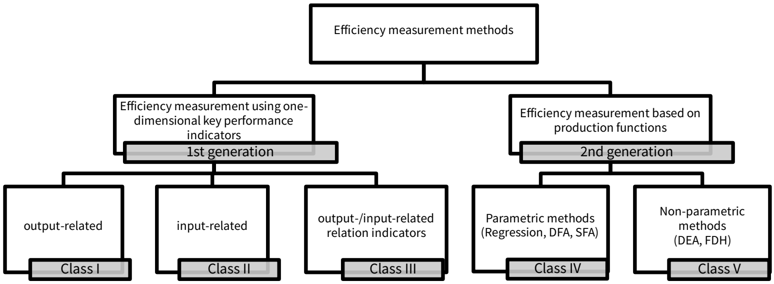

Figure 1: Efficiency measurement methods, adapted from (Hammerschmidt, 2006)

2.2 Technology quantity

The technology quantity T refers to all possible input-output combinations (Scheel, 2000). Figure 2 shows an example of a technology set as a shaded area. It results from the production function y = f(x), which is shown in the form of a straight line. Efficiency measurements that make use of a production function are to be assigned to class IV or class V. The input is defined by x and the output by y. Point A with the input quantity x_1 and the output quantity y_1 lies directly on the upper boundary of the production function and is therefore still part of the technology quantity as well as a possible input-output combination. Point C, with its input quantity x_3 and output quantity y_3, is also part of the technology quantity but is not on the upper boundary of the production function. Point B, with its input quantity x_2 and output quantity y_2, lies outside the shaded area and is therefore not part of the technology quantity. Point C is not a possible input-output combination. The production function y=f(x) shows which maximum output quantity can be achieved for a given input quantity. Similarly, for an expected output quantity, the minimum necessary input quantity can be identified. The linear course of the production function is freely chosen here and could also have a different course.

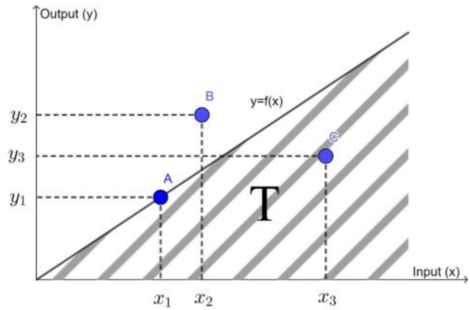

Figure 2: Technology quantity, adapted from (Scheel, 2000)

The technology quantity (T) in Figure shows the case of a single-input/single-output production system. A technology quantity is required for the 2nd generation processes based on production functions. A technology quantity is based on the assumptions of (1) empirical completeness, (2) economies of scale, (3) free wastability, (4) convexity (Scheel, 2000; Bogenstahl, 2012).

2.3 Parametric and non-parametric methods

In the following, the parametric methods are compared with the non-parametric methods in a short description. The decisive difference between the methods lies in the construction of the technology quantity. In parametric methods, a functional relationship between the inputs and outputs under consideration is specified a priori (Scheel, 2000). It should also be noted that in the case of multiple outputs, these must be combined into one output via prices. However, when constructing a production function of a parametric approach, in contrast to non-parametric approaches, stochastic data fluctuations can be considered. The result of a production function in a parametric approach reflects, therefore, the average of the examined units. Here, the non-parametric approaches distinguish themselves from the parametric approaches since they construct a best-practice line with their model-endogenous production function. Data quality is therefore of particular importance for non-parametric methods due to their high sensitivity with respect to data outliers. Table 1 summarizes the results of a bibliometric analysis for research applying non-parametric efficiency measurement, especially DEA, to warehouse setting, prepared by the authors as part of this study. The results indicate that research uses different inputs and outputs for various purposes and analytical objectives.

Furthermore, with regard to the status of knowledge, it can be seen that DEA is already being used in some areas of logistics. So far, however, no application can be found in food retail warehouse logistics over several periods. The factors for inputs and outputs are transferred from the existing research for the application in food retail warehouse logistics.

Table 1: Bibliographic analysis on DEA in warehouse logistics

no	author	Year	purpose	inputs	outputs
1	Dixit, A.; Routroy, S.; Dubey, S. K.	2020	measuring performance of government-supported drug warehouses	warehouse storage capacity, temperature-controlled storage capacity, number of skilled employees, operational cost	order fill rate, number of generic drugs, volume of drugs, consumption points, inventory turns ratio, time efficiency
2	Průša, P.; Jovčić, S.; Samson, J.; Kozubíková, Z.; Kozubík, A.	2020	performance of a logistic company with twelve warehouses is evaluated	number of pickers, average time of picking	annual income
3	Karande, A.; Krishna, A.; Jayasurya, R.; Gopan, G.; Gopinath, M. V.; Kumar, S.; Anoop, K. P.; Panicker, V. V.; Varaprasad, G.	2019	calculate the relative efficiency of warehouses owned by an Indian food grain procurement organisation	storage capacity, number of workers, number of wagons, working hours	monthly labour utilisation, monthly capacity utilisation

no	author	Year	purpose	inputs	outputs
4	Zeng, R.; Zhang, X.; Wang, P.; Deng, B.	2019	designs the performance evaluation system of warehouse operators in e-commerce enterprises	effective working rate	working quantity, working accuracy, working timeliness, working normalization
5	Raut, R.; Kharat, M.; Kamble, S.; Kumar, C. S.	2018	evaluating and selecting the most appropriate third-party logistics (3pl)	transportation charge per ton per km, fleet capacity/strength, vehicle type, and quality, driver rejection rate	percentage of target met by the 3pl, flexibility of a 3pl in providing vehicles, average time it takes for a 3pl to send his vehicles
6	Liu, J.; Gong, Y. Y.; Zhu, J.; Zhang, J.	2018	propose a new approach to conduct competitive environment analysis for a global operations strategy in retailing	the number of outlets; number of warehouses, number of suppliers	sales, market shares, ROI
7	Faber, N.; Koster, R.B.M. de; Smidts, A.	2017	explores fit among warehouse management structure and the context in which the warehouse operates	labour, size (scale 1-7), automation (scale 1-6), number of SKUs picked	production effective order lines, production special operations, flexibility (3-9 scale)
8	Lien, N.T.K.; Day, J.-D.	2017	evaluating 3pl companies specialize in integrated operation, warehousing and transportation services	assets, equity	net income, revenue

no	author	Year	purpose	inputs	outputs
9	Petridis, K.; Dey, P. K.; Emrouznejad, A.	2017	selection of a facility based on service level maximization and not just cost minimization	outgoing connections, total quantity sent	installation cost, fixed transportation cost from plant to warehouse, fixed transportation cost from warehouse to customer, variable transportation cost from plant to warehouse, variable transportation cost from warehouse to customer
10	Yang, C.; Taudes, A.; Dong, G.	2017	freight villages	total area, intermodal area, warehouse area, amount of investment	number of employees, amount of goods handled, no. companies attracted
11	Tang, L.; Huang, X.; Peng, Y.; Xiao, Z.; Li Y., Song H., Ren P.	2015	the paper constructed a "dea-tobit evaluation model" and introduced the mixed dea model	storage area, construction cost, facility cost, work hour, external cost	cargo throughout, pickup and delivery, effective use of the storage, order fulfillment
12	Li, H.; Ru, Y.; Han, J.	2013	an evaluation and identification approach examining a big soft drink company.	cost of sold goods, number of SKU sold, average inventory level, ratio for forecast orders/ real orders, delivery returns, forecast demand	number of customers served, revenue, product cases filled

no	author	Year	purpose	inputs	outputs
13	Andrejić, M.; Bojović, N.; Kilibarda, M.	2013	in order to improve discriminatory power of classical DEA models, PCA-–DEA approach is used	forklifts, employees in the warehouse, warehouse area, pallet places, electricity consumption, other energy costs (water, gas), utility costs, invoices (demands), warehouse overtime	deliveries, order picking transactions, order picking trans./order picker, turnover, warehouse space utilization, failures in the warehouse, write off expired goods, total failures
14	Pjevčević, D.; Radonjić, A.; Hrle, Z.; Čolić, V.	2012	efficiency measurement of ports over 4 years with the help of the DEA window analysis	the total area of warehouses, quay length, number of cranes	port throughput
15	Chakraborty, P. S.; Majumder, G.; Sarkar, B.	2011	operational, financial, quality	number of employees, general expenses, space, inventory	fill rate, sale, service time
16	Johnson, A.; McGinnis, L.	2010	to evaluated individual warehouses and groups of warehouses with regard to technical efficiency and to identify the operational policies, design characteristics, and attributes of warehouses that are correlated with greater technical efficiency	labor, space, investment	broken case lines, full case lines, pallet lines

no	author	Year	purpose	inputs	outputs
17	Mannino, M.; Hong, S. N.; Choi, I. J.	2008	evaluate an efficiency model for data warehouse operations using data from usa and non-usa-based (mostly korean) organizations	labor budget, computing budget	data age, change data, availability, queries, flexibility ratio, number of users
18	Jha, D. K.; Yorino, N.; Zoka, Y.	2008	analyze the performance of the distribution system in nepal by investigating the operational efficiencies of the distribution centers	distribution transformer capacity, feeder length, annual o&m cost, number of employees, distribution loss	annual energy sales, number of consumers
19	Hamdan, A.; Rogers, K. J.	2008	evaluate the efficiency of 3pl warehouses with unrestricted and restricted dea	labor hours, warehouse space, technology investment, material handling equipment	throughput (boxes shipped), order fill (boxes filled (for complete orders)), space utilization (cubic feet utilized)
20	Koster, M. B. M. de; Balk, Bert M.	2008	operational, quality	number of direct full-time equivalents, size of the warehouse, degree of automation, number of different skus	number of daily order lines picked, the level of value-added logistics (val) activities carried out, number of special processes, percentage of failure-free orders

no	author	Year	purpose	inputs	outputs
21	Korpela, J.; Lehmusvaara, A.; Nisonen, J.	2007	quality, financial	direct costs, indirect costs	reliability (time, quality, quantity), flexibility (urgent deliveries, frequency, special request, capacity (ability to respond to changes in warehousing capacity needs of a customer)
22	Min, H.; Jong Joo, S.	2006	financial	account receivables, salaries, and wages, expenses other than salaries and wages.	operating income
23	Ross, A.; Droge, C.	2002	equipment (capacity), operational	average labor experience, fleet size, equipment, mean order throughput time (mot)	product sales volume
24	Hackman, S. T.; Frazelle, E. H.; Griffin, P. M.; Griffin, S. O.; Vlasta, D. A.	2001	analysis of the operating efficiencies in 3 perspectives: the size of the warehouse, level of automation, and unionization	investment, total labor hour, square footage	accumulation, storage, broken case lines shipped, full case lines shipped, pallet lines shipped
25	Schefczyk, M.	1993	review two techniques (1. productivity rations 2. dea) to analyze the performance of industrial entities. performance analysis can be applied to a benchmark of facilities	labor hours, investment in material handling equipment	total number of correct transactions

3 Methodology

3.1 DEA and application requirements

DEA is a method for measuring relative efficiencies of decision-making units (DMUs) (Charnes, Cooper and Rhodes, 1978). DMUs can be very different depending on the application area of DEA. Individuals or teams, as well as entire companies or even national economies, can represent a DMU (Bogenstahl, 2012). In 1978, Charnes, Cooper, and Rhodes published their DEA model (Charnes, Cooper and Rhodes, 1978). This model was named the CCR model after its authors. Decisive for their work were the works of Debreu (Debreu, 1951), Farrell (Farrell, 1957), which dealt with the radial efficiency measurement and Koopmans (Koopmans, 1951), who did research on activity analysis. The first application requirement states that at least two decision units must be included in the analysis. Since the DEA is in the result about the evaluation of the relative efficiency of the decision units, it is necessary that at least two decision units are examined to be able to regard these to each other in relation. In addition, the quantitative relationship between decision units and inputs and outputs is of high importance for applicability (Dyckhoff and Gilles, 2014). The number of decision units must always exceed the sum of inputs and outputs. The reason for this lies in the endogenous weighting of the individual inputs and outputs. Therefore, despite multi-criteria consideration in an input-output combination, it is enough to show the highest efficiency. If the number of decision units is lower than the sum of all inputs and outputs, there is a risk that all decision units are efficient.

Comparability of decision-making units must exist (Dyckhoff and Allen, 1999; Scheel, 2000). Accordingly, only decision-making units whose transformation is comparable may be included in the efficiency analysis. The individual decision-making units must therefore have the same goals and use the same resources to achieve them. In addition to the decision-making units, the inputs and outputs must also be comparable. The literature points out that even if the inputs are apparently the same, it is essential to take a close look at them (Dyson, et al., 2001). The costs of a laboratory facility were apparently the same between the decision-making units. However, a look at the research, which was divided between the natural sciences and the humanities, made it clear that decision-making units in natural science research would always be less efficient as a result of the lower costs of laboratory equipment. The reference of the used data to the same period is also an important factor to be able to establish the comparability of the decision units. The last, but no less important, application requirement is the fulfillment of free wastability. This can be demonstrated by showing that there is no correlation between inputs and outputs. For this reason, a correlation analysis is created based on the determined data to make possible correlations recognizable.

In order to achieve a high informative value of the study and a sufficient amount of data, we use the data of one of the three largest German brick-and-mortar grocery chains operating more than 10.000 stores at the time of our data collection in 2021. Most data warehouse systems store inventory and sales data logs captured at a very detailed level. We use this data and aggregate it on a yearly level per the warehouse. Thus, our dataset contains all inputs and outputs used in the DEA model. Twelve warehouses for non-cooled perishable items were examined and used as the decision-making units of the efficiency analysis. The data was collected for the years from 2014 to 2020. The data used as inputs and outputs are listed in detail in Section 4.1.

3.2 BCC model

The BCC model is named after its originators, Banker, Charnes, and Cooper (Banker, Charnes and Cooper, 1984). They published their model in 1984, which, starting from the CCR model, is extended by one variable (Allen, 2002). These are δ_0. In the following, we note the BCC model with its corresponding constraints.

Mathematical notation of the BCC model:

$$\max E_0^{BCC-I} = \sum_{j=1}^{J} \mu_j y_{0.j} - \delta_0 \tag{2}$$

Constraints:

$$\sum_{k=1}^{K} w_k x_{0.k} = 1 \qquad (3)$$

$$\sum_{j=1}^{J} \mu_j y_{i.j} - \sum_{k=1}^{K} w_k x_{i.k} - \delta_0 \leq 0 \qquad \forall i = 1, \dots, I \qquad (4)$$

$$\mu_j \geq 0 \qquad \forall j = 1, \dots, J \qquad (5)$$

$$w_k \geq 0 \qquad \forall k = 1, \dots, K \qquad (6)$$

Figure 3 shows the comparison between the CCR model and the BCC model. The exemplary decision units represent the points A, B, C, and D. The CCR model with constant returns to scale forms the efficient margin with the dashed line through the origin and point B. Only point B is located on this edge and is, therefore, the only efficient point. The inefficiency of the remaining points can be measured by their respective distance to the efficient edge.

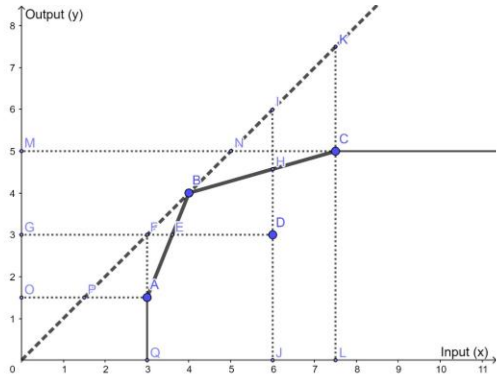

Figure 3: CCR and BCC model in the single-input/single-output case

3.3 Window analysis

In the DEA notation described so far, the decision unit data are each compared within the same period (Charnes, et al., 1985; Cooper, Seiford and Tone, 2007 ff.). Window analysis can nevertheless be used to compare decision units over several periods. A possible need for this tool may exist if no comparable decision units are available for a decision unit that can be included in efficiency analysis. To use Window Analysis, data over several periods must be available for the decision unit under consideration. The relative efficiency of the same decision unit over several periods can thus be determined, and positive or negative development can be shown. Window analysis can also be used when data is available for a large number of decision units over a large number of periods (Jia and Yuan, 2017). As part of the model formulation, the number of periods included in the analysis is defined. In the maximum form, an efficiency comparison of the decision unit with all other decision units is carried out over all periods. The minimum value would be the pure consideration within one period and would make the use of window analysis obsolete.

3.4 Super efficiency

Decision-making units that are efficient have a relative efficiency of 1.00 and are located on the efficient frontier. As already explained, many effective decision-making units can be found on this edge. The instrument of super efficiency makes it possible to differentiate these effective decision-making units (Andersen and Petersen, 1993).

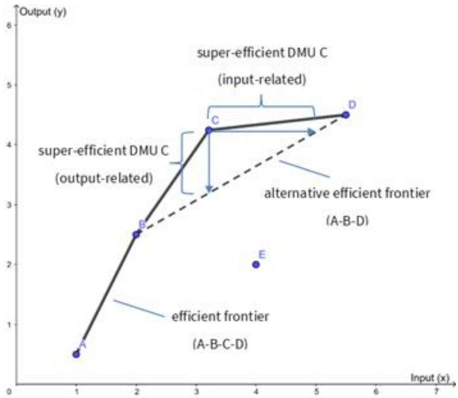

Figure 4: Super-efficiency in the single-input/single-output case

The decision-making units A to E are shown in Figure 4. Only decision unit E is not on the efficient margin determined by the BCC method and is therefore inefficient. To rank the efficient decision units based on super efficiency, an alternative efficient frontier (A-B-D) without C is formed. The distance from C to the alternative efficient frontier can be measured by input or output orientation. Accordingly, by the measured distance, the decision-making unit could increase its input quantity or reduce its output quantity and still be effective. For example, if a 15% reduction in output quantity were possible, the result would be a super efficiency value of 1.15 (Bogenstahl, 2012). All calculated super efficiency values can then be sorted in descending order, and a ranking of the efficient decision-making units is created. The assumption of an alternative efficient frontier is only used to calculate the respective super efficiency. If the removal of an efficient decision-making unit results in an alternative efficient frontier analogous to the original efficient frontier, the value remains at 1.00. The relative efficiencies of all inefficient decision-making units remain unchanged, as do all efficient decision-making units, which are still to be regarded as efficient despite the ranking by super efficiency.

3.5 Model selection method

The two models CCR and BCC differ fundamentally about their returns to scale. Depending on the use case, the result according to the CCR method with constant returns to scale is close to the BCC model with variable returns to scale. The question arises in which case the CCR model is sufficient and in which case a gain in knowledge is achieved by using the BCC model. This question can be answered, along with other methods, with the help of the Bankers test (Banker, 1996). A hypothesis test is used to determine whether the results differ significantly. The threshold value here is a 95% confidence interval. If the result of the calculation is above this value, the use of the BCC model is profitable about the information content and is, therefore, to be used.

4 Empirical Findings

4.1 Model formulation

The factors considered are divided into inputs and outputs. The results of the bibliographic analysis, which are shown in Table 1, were used to determine which factors have already been used as inputs and outputs. Derived from this are the parameters used in this study. It is important to note the different scaling of the factors and the consideration of non-monetary variables. In order to increase validity, 25 sources were used in the bibliographic analysis over a period of 7 years. Based on this analysis, the factors for the present research were chosen. The factors warehouse space, personnel costs, fixed material costs, and variable material costs are included in the analysis as inputs. Outputs included in the analysis are the number of orders processed, orders delivered too late, stores supplied, and incorrectly picked units, as well as inventory difference and average stock. The following assumptions have been made in advance of the calculation. The model is input-oriented, as all input factors are within the sphere of influence of management. The calculation is first performed with constant returns to scale and then again with variable returns to scale. The calculation is performed about the periods in one variant in isolation and therefore only in comparison to decision units of the same period. In another variant, the relative efficiency is calculated using window analysis over all seven periods. There is no exogenous restriction on the importance of weights. Finally, super efficiency is applied as a supplementary calculation method.

As inputs, we use the following parameters: (I_1) warehouse space (square meters), (I_2) personnel costs (euro), (I_3) fixed material costs (euro), (I_4) variable material costs (euro). As outputs, we use the following parameters: (O_1) number of orders processed (piece), (O_2) average warehouse load (euro), (O_3) inventory difference (euro), (O_4) number of orders processed too late (piece), (O_5) number of stores supplied (piece), (O_6) number of incorrectly picked units (piece). The inputs and outputs were validated using a bibliographic analysis of the DEA in warehouse logistics. This answers research question (1) about the components of an efficiency analysis for evaluating the performance of warehouses in brick-and-mortar retailing.

4.2 BCC model with window analysis and super efficiency

The final version of the model is the BCC model with the use of window analysis and super efficiency. The goal is to develop a model with high discriminatory power to create the highest possible informative value and optimization support for logistics. Starting from the basic models CCR model and BCC model, the BCC model was chosen. In the first step, it was extended by the Window Analysis. By adding super efficiency, the model could be further improved.

In Table 2, the changes to the model because of the use of super efficiency have been highlighted by bold formatting. A total of eleven values were changed. This means that 45 of 84 values have a relative efficiency of 1.00. This corresponds to a proportion of 54%. In this way, the application of super efficiency further improves the discriminatory power of the model. The eleven adjusted values are found in a range from 1.038 to 1.784. The mean value is 1.18. The value of "DMU 9" in the period 2018 was assessed with a super efficiency of 1.784. This is a very high value compared to the mean value of super efficiency. Another possibility for model adjustment would be to perform the calculation based on this outlier again without this decision-making unit. Since the relative efficiencies of the remaining decision-making units do not show a significant reduction in the calculation without window analysis in the 2018 period, it can be assumed that the new model would not differ significantly from the current model. In period 2014, only

"DMU 3" shows a changed value. In the period 2015, three changed values can be observed. In the periods 2016-2018, again, only two adjustments, and in period 2019, one adjustment can be seen. In period 2020, no change can be seen in the calculation of the super efficiency.

Table 2: Comparison of relative efficiency according to the BCC model with window analysis over all periods with super efficiency

	2014	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**Avg.**
DMU 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
DMU 5	1.000	1.000	**1.075**	1.000	1.000	1.000	1.000	**1.000**
DMU 7	1.000	**1.273**	1.000	**1.038**	**1.040**	1.000	1.000	**1.000**
DMU 3	**1.051**	**1.252**	1.000	1.000	1.000	1.000	0.970	**0.996**
DMU 4	0.966	0.982	1.000	1.000	1.000	1.000	1.000	**0.993**
DMU 6	1.000	1.000	1.000	1.000	0.882	1.000	1.000	**0.983**
DMU 9	1.000	1.000	1.000	1.000	**1.784**	**1.137**	0.805	**0.972**
DMU 10	1.000	1.000	**1.102**	**1.178**	1.000	0.638	0.873	**0.930**
DMU 8	1.000	1.000	0.940	0.826	1.000	0.739	0.729	**0.891**
DMU 11	1.000	0.914	1.000	0.825	0.843	0.885	0.758	**0.889**
DMU 2	0.972	0.950	0.857	0.815	0.730	0.634	0.604	**0.795**
DMU 12	1.000	**1.099**	0.891	0.797	0.632	0.651	0.586	**0.794**
Avg.	0.995	0.987	0.974	0.939	0.924	0.879	0.860	

Two particularly important findings emerge. The first finding is that, in the analysis to date, the decision-making units that exhibited a relative efficiency of 1.000 in all periods formed the efficient cluster. About the question of which units should serve as best practice examples and as models in practice, it has so far been possible to identify this efficient cluster clearly. Looking at the ranking structure, there is a widespread across the periods and decision-making units. Likewise, there is no dominant location within the ranks. The "DMU 7" site is most frequently represented with three ranks. The "DMU 1" decision unit, despite being consistently efficient, is not represented in the super-efficiency ranks. Accordingly, orientation in practice must be targeted to the best practice decision units, which are differentiated by super-efficiency.

The second important finding can be explained using the decision-making unit "DMU 12" as an example. In the consideration without super efficiency, this location is in the last group because of the low relative efficiency over all periods. Nevertheless, "DMU 12" reaches the seventh rank of super efficiency by the data in the period 2015. From period 2014 to period 2015, this decision-making unit was able to improve and then, after another five periods, only reached a relative efficiency of 0.586 and, therefore, the lowest value of the entire model. Although in this model for "DMU 12" in period 2015 the value is 1.099, the gap from period 2020 to periods 2014 and 2015 is still 0.414 in both cases. This reading accounts for the situation that all values above 1.000 were calculated by alternative efficient frontiers, but the efficient frontier of the model was not changed. In a similar form to "DMU 12", this can be seen in the decision-making units "DMU 3", "DMU 9" and "DMU 10". Looking at the 2020 period, no decision-making unit was able to transfer the special situation caused by the COVID 19 pandemic into an efficiency gain. If we look at the values, we can rather confirm the opposite. Of the decision-making units, which dominated in super-efficiency, sometimes significantly, in previous periods, only "DMU 5" and "DMU 7" can show a relative efficiency of 1.000. Increasing quantities lead to higher order sizes. This results in better conditions for higher picking performance. However, the rapid increase resulted in a strong short-term increase in the number of employees and adjustments to the working hours. The results of the analysis suggest that the resulting negative effects outweighed the positive volume effects.

4.3 Analysis of inefficiency by input factors

In addition to the relative efficiencies for each decision-making unit and input factor, the DEA provides a value by which the input factor would have to be reduced to be on the efficient frontier. The input factors of the inefficient decision-making units are projected to the efficient frontier. The resulting distance is used to calculate the necessary input factor reduction. In the model used, seven periods are considered for each of the decision-making units. At this point, the period 2020 is taken as an example. To be able to apply the findings directly in practice, the most recent period was chosen. In Table 3, the first column lists the decision-making units. The second column lists the relative efficiencies, which are sorted in decreasing order. In the following columns, the values for the corresponding input factors are entered. For a better reading, the input factors are shown in Table according to storage area "(I1) AREA", personnel costs "(I2) PC", fixed material costs "(I3) FIX MC" and variable material costs "(I4) VAR MC" shortened.

Table 3: Distances to the efficient frontier by input factor with window analysis in period 2020

DMU	rel. efficiency	(I1) Area	(I2) PC	(I3) fix MC	(I4) var. MC
DMU 1	0.1000	0 m^2	0T €	0T €	0T €
DMU 4	0.1000	0 m^2	0T €	0T €	0T €
DMU 5	0.1000	0 m^2	0T €	0T €	0T €
DMU 6	0.1000	0 m^2	0T €	0T €	0T €
DMU 7	0.1000	0 m^2	0T €	0T €	0T €
DMU 3	0.970	0 m^2	-1.306T €	-98T €	-34T €
DMU 10	0.873	0 m^2	-3.194T €	-38T €	-185T €
DMU 9	0.805	0 m^2	-2.405T €	-18T €	-293T €
DMU 11	0.758	0 m^2	-4.547T €	-69T €	-322T €
DMU 8	0.729	0 m^2	-3.276T €	-173T €	-353T €
DMU 2	0.604	0 m^2	-3.632T €	-227T €	-609T €
DMU 12	0.586	0 m^2	-4.929T €	-188T €	-1.236T €

The first five decision-making units in Table 3 are not to be considered for this analysis, as there are no input factor improvements to be made for these because they are efficient. For the remaining decision-making units, one similarity can be immediately identified. No reduction is allocated to the input factor storage space. This assessment arises because the input factor was assigned a fixed value in the model because warehouse space cannot be adjusted in the short term.

Furthermore, the input factor personnel costs are assigned the highest savings values. The high absolute values of personnel costs in the input data compared to fixed and variable material costs can be attributed to this. The decision-making unit "DMU 3" with a relative efficiency of 0.970 would have had to save personnel costs of 1,306T€, fixed material costs of 98T€, and variable material costs of a further 38T€ in period 2020 to be efficient. The decision-making unit "DMU 12" with a relative efficiency of 0.586 would have had to save personnel costs of €4,929T, fixed material costs of €188T, and variable material costs of a further €1,326T in period 2020 to be efficient. In total, this amounts to 6,353T €. These values can be used in practice for adjustments in the areas. This could result in adjustments to the warehouse layout, the picking method, the staffing of incoming and outgoing goods, the performance specification for picking, or the conditions of service providers, to name just a fraction of possible approaches for improvement. By quantifying the reduction to be aimed for according to input factors, the target definition is already available as probably the most important part of a measure to increase efficiency. Based on the individual input factors and their calculated values by the DEA, target values are defined for all inefficient decision-making units. Another way to use the results of DEA is the following approach. “DMU 12” has been selected as an example here because the most significant change in relative efficiency can be observed in this DMU.

Table 4: Distances to the efficient frontier by input factor with window analysis of the DMU 12

Year	**rel. efficiency**	**(I1) Area**	**(I2) PC**	**(I3) fix MC**	**(I4) var. MC**
2014	1.000	0 m²	0T €	0T €	0T €
2015	1.099	0 m²	0T €	0T €	0T €
2016	0.891	0 m²	-885T €	-119T €	-168T €
2017	0.797	0 m²	-1.783T €	-166T €	-329T €

Year	rel. efficiency	(I1) Area	(I2) PC	(I3) fix MC	(I4) var. MC
2018	0.632	0 m²	-3.612T €	-212T €	-661T €
2019	0.651	0 m²	-3.761T €	-180T €	-784T €
2020	0.586	0 m²	-4.929T €	-188T €	-1.236T €

The manager responsible for only one of the eleven decision units can use this form of results over the course of the period for decision-making. The decision-making unit "DMU 12" is listed as an example of this. In addition to the possible measures already mentioned in the area of personnel costs, some starting points for influencing the two input factors in the area of material costs should be mentioned here. The implementation of investment measures leads to depreciation costs and, therefore, to fixed material costs. Each measure must be evaluated in light of the operational necessity and the economic benefit. For example, higher depreciation costs can make sense if this results in a more than the proportional reduction in maintenance costs. Maintenance costs are one of the components of variable material costs that can be influenced the most. Especially in variable material costs, a regular review of the classic make-or-buy decision can always be part of the measures. By using DEA, the comparison succeeds beyond monetary limits and still brings clear target values around monetary influenceability. These two approaches answer the research question (2) about the main potentials for the examined warehouses when aspiring to increase their performance.

5 Discussion

5.1 Implications for practice

Our empirical examination on warehouse efficiency for a large German brick-and-mortar chain pointed out that DEA is suitable to assess the efficiency of warehouses for non-cooled and perishable items. For logistics managers, this spawns a way forward to reach multi-criterial efficiency measurement aggregated to one efficiency score. Compared to traditional one- or two-dimensional benchmarking, our methodology enables the integration of several perspectives. Furthermore, our methodology can spawn interesting insights for logistics managers of all levels as the selection of DMUs is highly flexible in DEA. While choosing warehouses as DMUs has a more strategic character on a high aggregation level, the evaluation of trucks in one depot may be used as a benchmarking approach on a more operational level. In summary, while the model formulation has to be adjusted to the purpose of the analysis, our non-parametric DEA model is in general suitable to address management questions of several hierarchy levels from middle to top management.

For further research, logistics managers should consider adjusting the periods to monthly observation. It is recommended to develop a model that is designed with input and output factors only by controllable variables. This change of perspective from the perspective of total costs to a construct of monetary and qualitative factors that can be influenced would run against a behavioral model that is typical in practice. This is shown by pointing out the negative developments of factors that cannot be influenced by managers.

5.2 Implications for theory

From a systems theory perspective, our examination shows that DEA is suitable to measure the efficiency of complex systems operating with various inputs and outputs. For these systems, the degree of internal understanding for the throughput process is limited, often leading to black box assumptions. Because simple or advances parametric methods use various assumptions when evaluating these black box scenarios, the non-parametric DEA with model-endogenous factor weighting is suitable to deal with complex systems. For panel data, the combination with the window analysis, an instrument would be created that makes it possible to visualize the success of the implemented activities over the monthly course of the periods under review. Even with this application option, nevertheless, there are points of attention. Because the monthly presentation of results is used for internal reporting, it does not have to satisfy the legal requirements of external reporting. This results in the risk that not all costs are accounted in the correct period. The use of DEA would therefore require a high level of period-by-period accounting to ensure that the validity of relative efficiency as an aggregation of all factors is not questionable.

Further research avenues may include the integration of shareholder and stakeholder perspectives through an AHP-based pre-factor weighting of the inputs or outputs used in the DEA model. While the model-endogenous factor weighting is a major advantage of DEA, the output of, e.g., on-time delivered transport units, may be 0.00001. Because this may not be in the interest of stakeholders, e.g., the grocery stores, AHP-based pre-factor weighting can avoid this shortcoming of traditional DEA models. Last, the traditional and deterministic DEA models explained above require the availability of exactly known values for the specified input and output measures. Hatami-Marbini et al. (Hatami-Marbini, et al., 2017) argue that this kind of model is susceptible to changes or errors in data values. As the data in real-world problems tend to be imprecise or vague, researchers have been working on DEA models that aspire to deal with uncertain input and output data. Therefore, an interesting further research avenue may include the efficiency measurement of warehouses through fuzzy DEA.

6 Conclusion

Based on data from 12 logistics centers, a multi-criteria efficiency analysis was performed over a period of 7 years. The weighting of the factors was done model endogenously by DEA. The BCC model with variable returns to scale was used as the base model. It was extended to include Window Analyses to provide a cross-period efficiency comparison. In addition, the super efficiency was included to increase the discriminatory power of the model. As a result, an exact value was presented in the input-orientated model for all input factors. This value must be saved to make logistics efficient in relation to the others. A further consideration is the creation of an output-oriented model, as well as a model with factors that can be completely influenced by the responsible managers.

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