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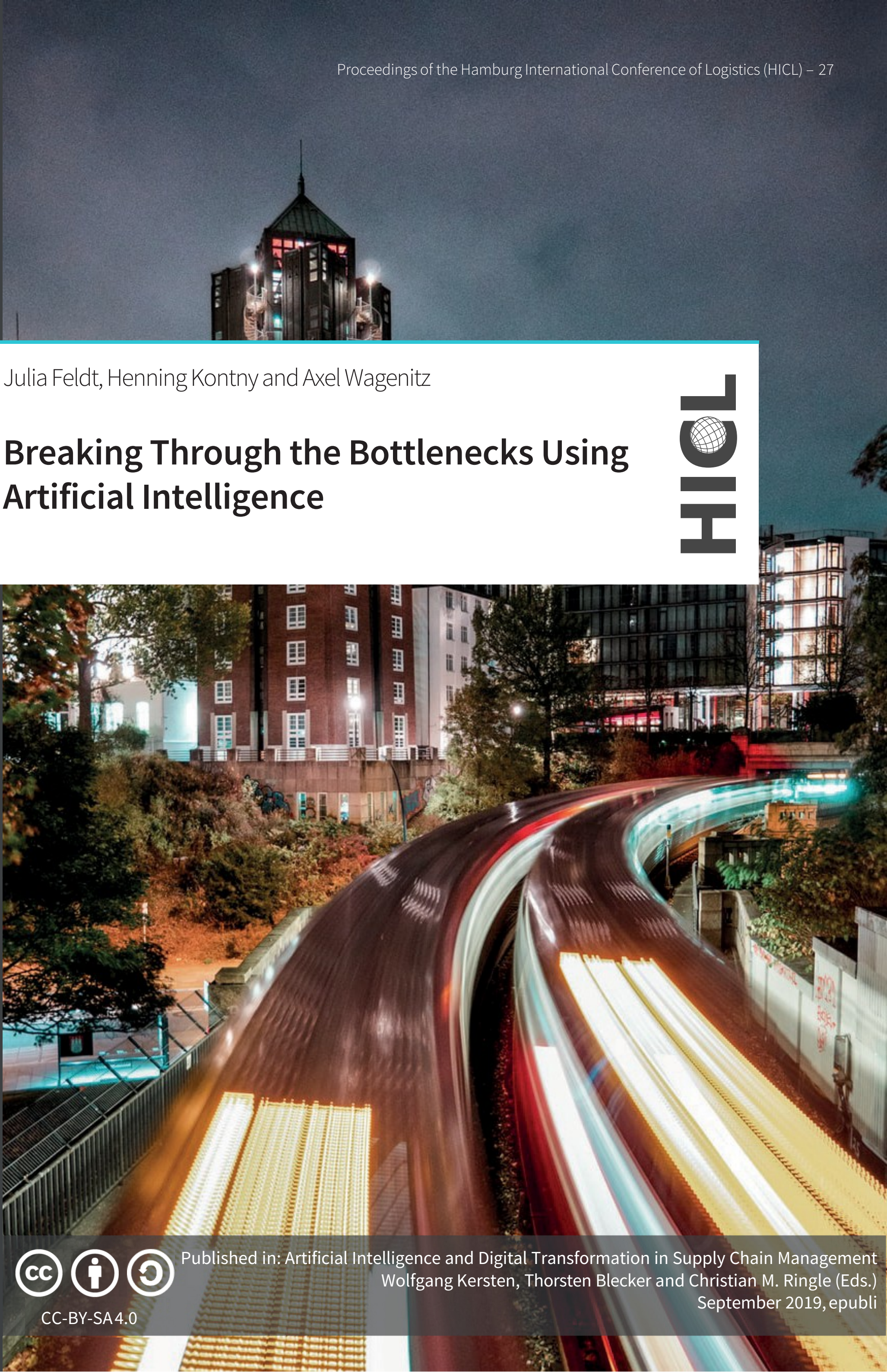

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# Breaking Through the Bottlenecks Using Artificial Intelligence



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# Breaking Through the Bottlenecks Using Artificial Intelligence

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**Purpose:** Performance of Supply Chain is highly dependent on weak spots, so-called bottlenecks. This research paper presents the findings from the analysis of operation processes of a mid-sized producing company and the digital solution for opening up the bottlenecks in order to achieve effectiveness by cutting down the order lead time.

**Methodology:** The study is employing several rounds of simulation based on processes and data from a manufacturing company.

**Findings:** Simulation results demonstrate that by allowing a system to take autonomous decisions for production planning based on current changes in environment such as new customer order or available capacity, the order lead time can be shortened significantly, while granting additional flexibility and robustness to the whole supply chain.

**Originality:** The findings of this research reveal new insights on potentials of artificial intelligence in solving of existing issues within supply chain IT systems.

**Keywords:** Artificial Intelligence, Assembly-to-Order, Bottlenecks, Supply Chain

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# 1 Introduction

Recent developments such as Internet of Things (IoT), Industry 4.0, Artificial Intelligence (AI) and other digital technologies are transforming Supply Chains, allowing them to operate based on autonomous decisions analyzing collected data in real-time modus. Thus, granting access to previously inaccessible software solutions and new levels of automation (Calatayud, Mangan and Christopher, 2019; Shmeleva et al., 2018). Consequently, information that was formerly collected by humans will gradually be machine-generated, allowing more precise decisions as well as faster reactions to any disruptions, changing supply chain into a robust interconnected system (Buxmann and Schmidt, 2019; Monostori et al., 2010). Future supply chains will be able to steer themselves continuously, monitoring the environment and react to changes, autonomously learning from previous situations and simulating possible scenarios, developing advanced dimensions of flexibility and agility (Fisel et al., 2019; Tjahjono et al., 2017; Wagner and Kontny, 2017).

Despite all the promising gains, there is still no confidence in what artificial intelligence stands for. In popular cultures, such as Chanel 4's series "Humans", the focus lies on mimicking humans, which may be the long-term goal of research on machine intelligence. Still, current research should be focused on the more practical use of artificial intelligence, such as support of humans in decision-making processes in everyday operations in the form of self-learning software instead of focusing on a recreation of a workers body (Tredinnick, 2017). According to the Accenture Study (Plastino and Purdy, 2018), manufacturing is one of the three most meaningful sectors, which would benefit from AI technologies in the next years, since AI could provide tremendous support in dealing with an increasing number of product types, customization and other growing customer expectations (Lv and Lin, 2017). Given the circumstances that supply chains are confronted with disruptions daily, companies should aim to increase their flexibility by development and implementation of AI solutions customized to the company-specific operations (Scholten, Sharkey Scott and Fynes, 2019).

This paper aims to present the AI-based assembly-to-order supply chain solution for a mid-sized manufacturing company and thus, to make a contribution to the research with practical focus as well as provide support for companies, searching for the ways to improve their operations.

# 2 Theoretical Background

## 2.1 Definitions and History of Artificial Intelligence

There are many different definitions of Artificial Intelligence, referring to it as:

“a cluster of technologies and approaches to computing focused on the ability of computers to make flexible rational decisions in response to often unpredictable environmental conditions” (Tredinnick, 2017),

“a subject that studies theories, methods, and applications with respect to simulation, extension, and expansion of human intelligence for problem-solving. AI aims to understand the essence of intelligence and design intelligent machines that can act as human behavior” (Niu et al., 2016),

“AI concerned with creation of computational system that imitates the intelligent behavior of expertise” (Leo Kumar, 2017).

Other Authors emphasize that AI systems “can learn by experiencing, universalize where direct experience is absent, and map from the inputs to the outputs” (Mohammadi and Minaei, 2019; Chaturvedi, 2008). At the same time, the authors agree that machine learning should not provide the same level of complexity as human learning (Niu et al., 2016; Mohammadi and Minaei, 2019).

In order to develop a better understanding of the definitions of artificial intelligence, a summary of essential step stones in its history is provided below. Already in the 1940s at the start of computing, the idea of “machine intelligence” was discussed. In 1950s, Turing described the famous “Turing Test” for the test of machine intelligence, claiming that “by the end of the century it will be possible to programme a machine to answer questions in such a way that it will be extremely difficult to guess whether the answers are being given by a man or machine” (Tredinnick, 2017). Some years later, in 1956, John McCarthy introduced the term Artificial Intelligence, arguing that a machine could solve problems and improve itself on the same level as a human being (Leo Kumar, 2017). Some researchers (Tredinnick, 2017) suggest, that the first big step towards AI was Eliza, the chatbot from Joseph Weizenbaum, demonstrated in 1966 for psychotherapeutic conversations with people. Despite the success, it took researchers another 30 years till in 1997 the IBM’s Deep Blue famously won a chess game with world champion Garry Kasparov. Later, in 2011, the quiz show Jeopardy was played by IBM’s Watson, marking with its win the intelligence to analyze unstructured data to find answers to questions, asked in “natural” language. Three years later, 2014, chatbot named Eugene Gootsman could persuade 1/3 of the jurors that it is human (Tredinnick, 2017).

Presently, AI solutions have been successfully tested in areas such as autonomous unmanned vehicles, medical diagnosis, speech recognition, video games and others (Mohammadi and Minaei, 2019). Although the focus turned away from a very general simulation of the human brain toward problem-solving in a real work environment, i.e.:

- Speech recognition,
- Semantic reasoning,
- Machine learning ("the ability to improve at performing tasks on the basis of iteration"),
- Intelligent data processing (Tredinnick, 2017).

In order to support assembly processes, this article focuses on the last two application since they are most interesting for autonomous decision-making.

## 2.2 Related Work

Although the researchers do not provide a clear statement on how the Artificial Intelligence (AI) in manufacturing is defined in comparison to Machine Learning (ML), they agree that both concepts are valuable for the Industry 4.0 and especially for the operations, regarding to it as a Smart Factory which uses "new innovative developments in digital technology including advanced robotics and artificial intelligence" (Tjahjono et al., 2017).

Daehn and Taub (2018) introduce the concept of "Robotic Blacksmith" in order to investigate the ways of using an autonomous system based on closed-loop Machine Learning for metal forming within metamorphic manufacturing, which includes all metal forming operations. The authors provide a general framework and two case studies with a 3D simulation of a corresponding practice. One of the main benefits outlined in the study is the ability of measurement of the environment with sensors, precise control of actions and thus the reproducible results, which are especially essential in industries working with safety-critical products, such as aerospace and nuclear. Another benefit is lower energy consumption of the machine-based solution in comparison to “classic” manufacturing or additive manufacturing.

Mourtzis and Doukas (2015) provide two case studies from automotive industry with highly customized products using the concept of Artificial Intelligence, arguing that in a very complex global supply chains some decisions are nearly impossible to calculate, since the number of possible solutions even for a simple case is calculated at 12,266,496 and in more complicated situation at 48x1017. Such high complexity in decision-making processes, as well as the need for real-time information, makes the Machine Learning or Artificial Intelligence technologies indispensable for (self)-adaptive Smart Supply Chains.

Monostori (2018) indicates increased transparency as well as higher robustness of supply chains through faster identification of the probable disruptions by use of cyber-physical solutions. Verdouw (2016) illustrates such an increase of transparency on the example of food supply chains in general and fish distribution in particular. Furthermore, supply chains can achieve robustness and competitiveness by the implementation of adaptive and IoT-based solutions where decisions made by machine-intelligence will be aligned with high-level decisions taken by humans as explained in the mathematical programming model from Rezaei et al. (2017).

Other authors (Wu et al., 2016) state that the use of the above technologies transforms supply chains into Smart Supply Chains (SSC) with six unique characteristics:

- Instrumented; information is mostly obtained by machines using sensors, RFIDs etc.
- Interconnected; the entire operations and assets are connected.
- Intelligent; SSC optimizes their performance by taking decisions.
- Automated; most of the processes are automated in order to replace less efficient resources.
- Integrated; information is shared across all SC departments;
- Innovative; new solutions will be developed to solve any occurring issues.

Despite the acknowledgement of all the positive characteristics of the intelligent solutions, Jede and Teuteberg (2016) warn about the challenges of their implementation across the supply chain. They argue that researchers should pay more attention to the security aspects, explore the technical details such as interface configuration among different SC partners and definitions of connections between sub-processes in order to provide valuable support for practitioners. Others, (Merlino and Sproģe, 2017) predict that in near future smart factories supported by artificial intelligence and IoT "will make running a supply chain as easy as pushing buttons".

# 3 AI-Based Assembly-to-Order Supply Chain

## 3.1 Project Phases

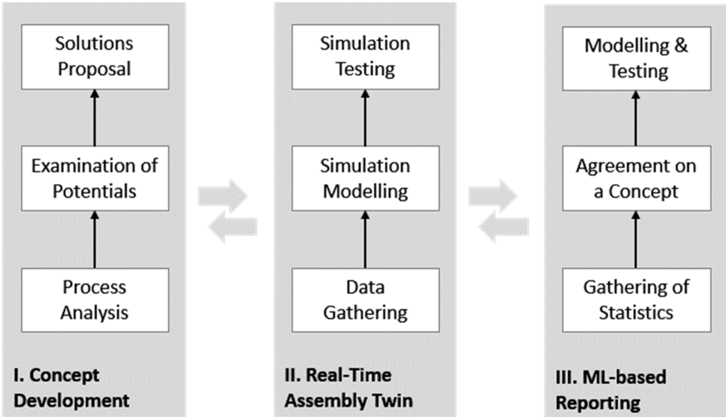


Figure 1: Project Phases

In order to make the project manageable and trace the progress of significant mile-stones, it was divided into three phases (as shown in Fig.1):

- Concept Development
- Modelling of working Real-Time Assembly Twin
- Use of Machine Learning based Reporting.

The overall process is iterative, which means that despite the clearly defined process order, some steps were performed more than once. For example, after simulation testing in phase II, the solutions proposal undergone various changes. Each phase is described in a corresponding chapter below.

## 3.2 Planning Processes as Main Source of Bottlenecks within the Supply Chain

The first step of concept development was to provide an analysis and description of all the Supply Chain processes of a company, which is a leading company in filter fans production. Although the company has other products such as alarm lights and electronic devices, the focus has lied on filter fans. High-level Supply Chain of the company is quite similar to many manufacturing companies; it consists of different independent departments:

- Purchasing (Raw Materials, Spare Parts and Packaging)
- Production of Components (Molding of Plastic Components as Mass Production)
- Assembly (in Assembly Cells using workforce)
- Warehouse (Stock Management, Transportation, In- and Outbound Logistics).

After a deep-dive into processes, the following conclusions were made:

- Customer orders contained no seasonality, and demand is quite stable from month-to-month (max. deviation 18%, mostly based on delivery of big orders in containers in overseas).
- Order-Lead-Time in most of the cases was around three weeks.
- Minimal production time per batch (several hundred pieces) is one hour (plus 1-2 hours to change molding components).
- Average assembly time 6 minutes per product.
- Stock levels for finished goods are unnecessary high (approx. 5 weeks)

All planning processes (Production Planning, Assembly Planning, Human Resource Planning) are performed in different departments in different Excel sheets (Wagner and Kontny, 2017). The High-level intercompany supply chain is shown in Fig.2, where the order-lead-time (here as the time from customer order in ERP system to the point, when finished goods are shipped) was used to define main Bottlenecks. The left side (As Is Supply Chain) shows the order lead time for the planning processes with the support of Excel sheets. Once per week assembly planners (each is responsible for different products) decide on volumes for the assembly planning for the next four weeks. Mainly basis for the decisions is information on available stocks (should products be delivered from available stocks or manufactured) as well as available workforce. Then, two days later, similar process takes place within a production department, which produce the spare parts for the assembly. At the end, purchasing planners will decide if they need to order raw materials for production or spare parts for the assembly. Despite the fact that the logic of such a decision is always the same (with given priorities), there was no automated solution implemented, which lead to unnecessarily extended order-lead-time of approx. three weeks. IT-based solution with the capacity to take decisions in (near) real-time modus would allow synchronizing of all planning processes along the supply chain at the same time significantly shortening the order-lead-time by at least half.

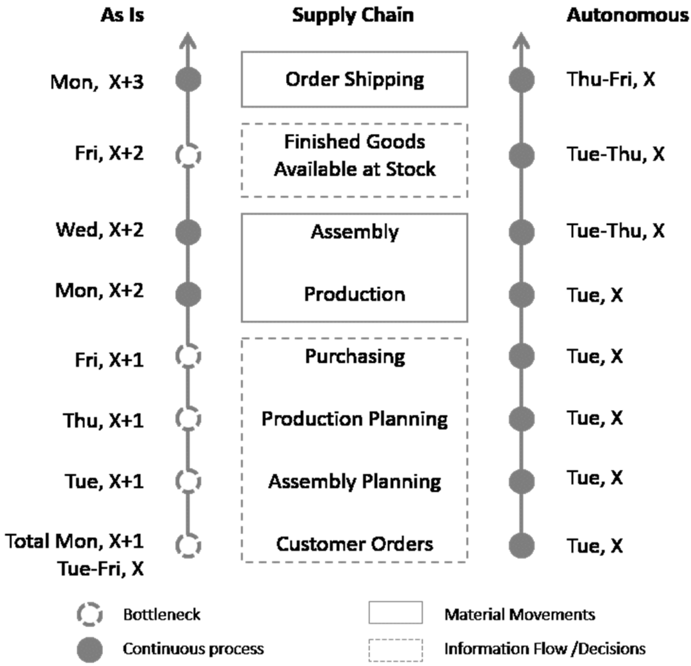


Figure 2: Bottlenecks based on Order-Lead-Time

Since the production as a process step is more time-consuming and less flexible than assembly due to time- consuming retooling of machines as well as a high volume of production batches, the assembly process was chosen as a central process, which provides others (purchasing, ware-house, production) with information relevant for their process steering. Such an approach is not new and is widely known as Assembly-to-Order (Mourtzis and Doukas, 2015) or Build-to-Order Supply Chain (Gunasekaran and Ngai, 2005). The main difference between the "classical approach" and the presented solution is the focus on automated information flow and shortening of order-lead-time instead of material movements and stocks.

The last bottleneck, which is based on a delay of goods availability according to the ERP system and goods produced, can be quickly resolved by scanning of the goods directly at assembly cell and creating additional virtual warehouse in ERP. Thus, the goods can be shown as available, before they will be shipped to the central warehouse, which will spare at least two additional days.

## 3.3 Solutions Proposal

Based on the fact, that assembly processes could have the most flexibility in capacity if needed (increasing from usual 100% to 400%) being at the same time the slowest process (planning processes take in average over one week), it was decided to improve the assembly planning.

Another critical argument for the automation of assembly planning is provided by Knoll, Prueglmeier and Reinhart (2016), who states that a planner uses only 20% of his time to perform planning, whereas 50% are used for data gathering and preparation. They provide three reasons for such an unfortunate time split:

- Lack of software support
- Inconsistent information
- Unavailable historical data.

In the presented case, the lack of software support leads to extensive use of Excel-Sheets by planners in each department, with data matching at jour-fixe once per week. Since the data in operations changing continuously, such work methods are very inefficient and inevitably lead to high stock level and or to the high level of delayed deliveries. Thereby the lack of software support drive towards different information status in each department and thus to inconsistent information, i.e. stock level in Excel-sheet do not display real stock level in the warehouse, open orders only consider customer orders from previous day. Moreover, ERP only shows the actual status of data and do not provide tools for the analysis of historical data. Such analysis was done only from time to time in Excel, and results were not always shared between departments, leading to a different level of professional competence in different departments by different employees.

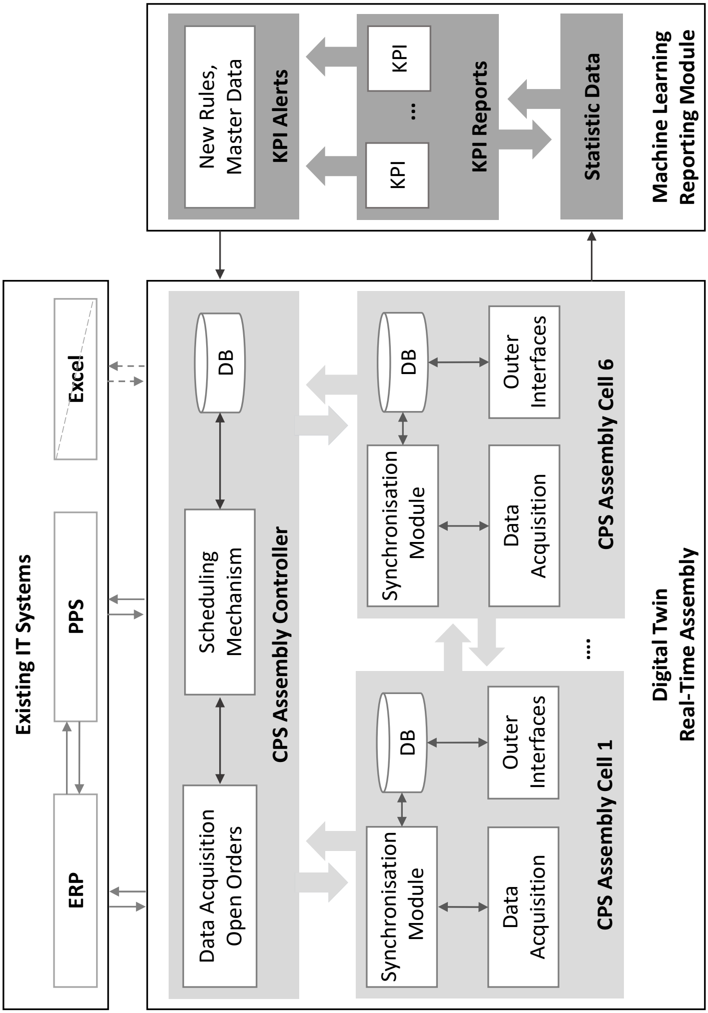


Figure 3: AI-Based Solution for the Bottlenecks

In order to enable planning processes in real-time (or near-real-time) modus with same information status at all process levels as well as the same quality of information, two solutions were created (as shown in Fig.3). Lack of software support, as well as inconsistent information, can be solved by the Real-Time Assembly Twin (Project Phase II), whereas unavailable historical data require advanced reporting module (Project Phase III).

The main distinction between Real-Time Assembly Twin and Machine Learning Reporting Module is time horizon. First concentrates on a continuous simulation of discrete events without data gathering directly in the tool (although some data is forwarded towards ERP). Second, on the contrary, should gather historical data and even overwrite the initial logic/rules for the Assembly Twin shaping it into self-learning and thus AI-based system.

## 3.4 Real-Time Assembly Twin

### 3.4.1 Functionality

Real-Time Assembly Twin was created and tested in order to support planners and workers in the assembly area. Additionally, it provides information on the current status of orders to other departments, such as warehousing and in-house transportation.

The system consists of 7 modules, one for each available assembly cell and one with controlling function (Assembly Controller, as shown in Fig.3). Assembly Controller takes the data on open orders from ERP and "translate" them via Scheduling Mechanism into Assembly Orders for each Assembly Cell. All data, needed for the scheduling, such as which cell should assembly which products, production capacity and other relevant data are stored up in the Data Bank of Assembly Controller. Each Cell shows the worker in the assembly cell the orders at the monitor, allowing the worker to update the status of each order, by pushing the button "finished" on the screen or by logging out (thus saying, there is no available worker in the cell). Since in each cell can work up to two employees in two shifts and each worker is able to assemble any product, which means he can freely move from one cell to another, the flexibility of the process is incredibly high. Unfortunately, by planning all the assembly orders weeks upfront, as it was done previous, this flexibility was seldom used. However, with the planning system in (near) real-time modus, it is possible to calculate available resources against open orders, creating a robust and flexible process.

At the end of the period (day or shift), the Assembly Controller gather the data from each cell and communicate it to the ERP, saving open orders for the next day.

### 3.4.2 Data Gathering

According to Uhlemann (2017), data gathering represents one of the most critical stages for modelling of a Digital Twin. Non-volatile data such as warehouse layouts, process descriptions, historical data and assembly specifications were collected during face-to-face interviews and workshops, with confirmations on the correctness of the results over the phone or via email. Volatile data, i.e. data on material movements, order volume, available stocks, were collected directly from the ERP system. Real-time modus of the digital twin of the assembly could be achieved only by using the data directly from ERP; otherwise, the general data from reporting system is already too old, since it shows the data from the day before. In summary, it can be said that data gathering is a very time-consuming process which is essential for the proper functioning of a new system.

### 3.4.3 Simulation Modelling

As described in Chapter 3.3, the Real-Time Assembly Twin is basically a simulation which is used to replace the non-existing operational system and for which the existing research method of simulation modelling was chosen as most appropriate.

According to Wojtusjak (2012), simulation techniques can be applied for modelling of complex systems since they can recreate the true-life system's performance. The discrete event simulation (DES) offers an opportunity to trace the alterations of a model with logical multiplex configurations by data-gathering after a defined "event" took. It contains three modifications: activity-oriented, process-oriented and event-oriented simulation. DES can be applied for systems which represent a "set of interrelated entities which only change their state at discrete points of time as a result of their behavior or the behavior of other entities" (Ullrich and Lückerath, 2017). This simulation method is broadly used for the simulation of production processes (Gong et al., 2017), which makes it suitable for our case with assembly-planning.

In the presented simulation of the assembly, the "trigger" events are either start/end of the day/shift or new customer order or change/deviation to the planned capacity in each assembly cell. At the start of the day X the tool translates open orders from the ERP system into assembly orders, creating a list of assembly orders different for each assembly cell. New customer order(s) lead to amendments in open assembly order(s), depending on the bill of materials from ERP and master data of an assembly cell. Previously unexpected changes in available capacity, i.e. if a worker did not show up in the morning due to illness or if a person new to a job works below the usual productivity level, the Real-Time Assembly Twin will consider it in a calculation and make a request to other assembly cells for the additional workforce. On the other hand, during the assembly process each assembly order will be reported to the ERP system as finished, after the worker pushed the finished button on his screen, allowing the system to update the data in near real-time modus and if needed to forward the information to other SC processes, i.e. for the warehouse or goods departure area.

In order to duplicate the sequence of all steps within assembly planning as well as analyze the data from ERP and other systems, the existing OTD-NET simulation software was significantly changed. OTD-NET is the award-winning software, which was built at the Fraunhofer Institute of Material Flow and Logistics for the simulation of production network of big automotive companies such as Daimler AG and Volkswagen (Motta et al., n.d.; Li and Fang, 2012; Liebler et al., 2013). The original software was customized to the logic and supply chain of the manufacturing company.

### 3.4.4 Verification and Validation

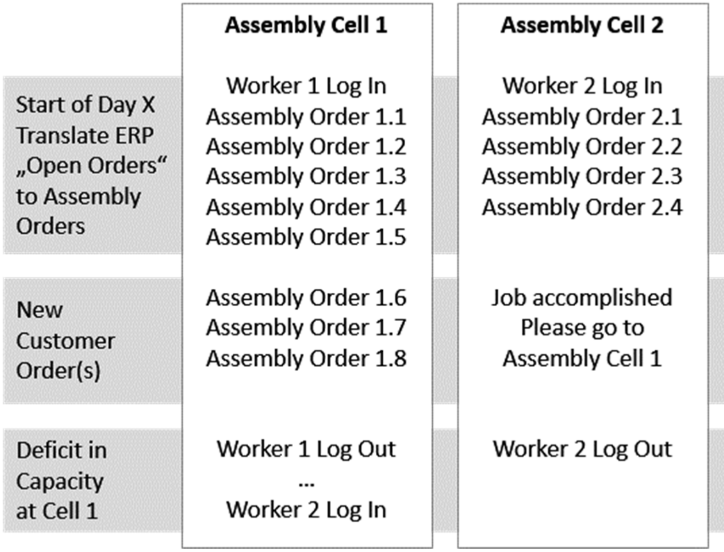


Figure 4: Assembly Interface and Simulation "Triggers

Verification can be defined as “ensuring that the computer program of the computerized model and its implementation are correct”, whereas validation referred to as “substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model” (Sargent, 2005). In other words, validity is measured concerning the purpose of the created model; if its accuracy lies within an acceptable range, the model can be concerned as valid.

In order to create new functioning systems, three steps were performed:

- Conceptual model validation
- Computerized model verification
- Operational validation

Conceptual model validation was carried out by respective assembly planning personnel, confirming that the described processes and assumptions are correct and can be executed as planned. Computerized model verification was performed on both sides: by the IT department of the company as well as the research team. It was divided into two steps; first, the “static testing” verified the correct structure of built Digital Twin, and then, by running simulations on company’s historical data the “dynamic testing” verified its functionality. Operational validation was performed on a data from ERP in order to measure the time, needed for re-planning of assembly orders (which lied under 1 Minute), to confirm that the “translation” is correct, and no data was lost in the process and to prove the functionality of user interface (for an assembly worker).

## 3.5 Machine Learning-Based Reporting

Machine Learning (ML) can provide a basis for the assembly planning since there is high volume on “high repetition of recurring planning tasks for each material number caused by frequently changing information” (Knoll, Prüglmeier and Reinhart, 2016). This way, ML provides the best use of historical data with minimal effort.

As shown in Figure 2, the planned ML-based Reporting Module should work inde-pendently from the Real-Time Assembly. The reason for such separation is that in order to function correctly, the ML Reporting Module should first create a proper Database with statistic data. On the one hand, it will take at least a year, in order to have enough data, for reasonable planning. On the other hand, it will allow to create alerts for unusual situations (which are covered today by so-called security stock of goods) as well as rewrite current Master Data and Rules in Assembly Controller. For example, gathering information on current assembly time for product Y and comparing it with historical data on assembly time, the assembly time in the individual cell could be overwritten, providing more precise information on available capacity in this cell. Since assembly time can differentiate even by the same person from one day to another, such adaption would allow very precise planning. Additionally, the Reporting Module will allow to analyze the work of Real-Time Assembly and measure which impact it provides for the Assembly Planning as well as for the stock levels and another necessary logistic KPIs.

# 4 Discussion of Results

## 4.1 Implications for AI and SCM Theory

Previous research implied that there is a direct correlation between the rise of complexity and decline of the possible level of agility of the supply chain (Giannakis and Louis, 2016; Monostori, 2018). Application of an AI solution within the supply chain can be very efficient under such circumstances, allowing companies to react very fast to unexpected events and restart a planning process as often as needed. This way, even big companies with complex operations can stay agile and competitive without the unnecessary explosion of bureaucracy.AI and IoT technologies most frequently referred to when discussing the development of autonomous supply chain systems. Capability to analyze high volumes of data and solve complex problems make AI indispensable for future Supply Chains and thus for the research in this area (Calatayud, Mangan and Christopher, 2019).

The presented paper describes a process of finding the appropriate application area for an AI solution as opposed to the approach of the application of standardized IT tools which seldom reflect the specific requirements of an individual customer. Furthermore, we propose to split the AI solution into two parts, one responsible for the quick decisions and the other for historical data as well as steering rules. Although the simulation results could not be presented to broader public since they are based on the company data which are prohibited from publishing, the provided framework can be used by other researchers in the area.

## 4.2 Practical Implications

Presented solution for the assembly planning has implications on the whole supply chain:

- Order-lead-time shortens from three to one week.
- Stock levels go down automatically since the tool decides if the goods should be assembled or delivered from warehouse and due to shorter order-lead-time the finished goods, as well as spare parts will not be stored in-between, waiting for the next process step.
- Customer order can be translated into an assembly order within seconds/ minutes instead of once per week.
- Workers in the assembly have a clear overview of their orders and can report comple-tion of an order directly to the system (instead of previous paperwork).

Other processes such as logistics, purchasing and production can be provided with information on current status of assembly /stock level instead of outdated plans.Despite the high-level of presented information, it can be used by practitioners as a blueprint for the first steps in similar projects.

## 5 Summary

Although the terms of Artificial Intelligence and Machine Learning are discussed for almost eighty years, the development of real-life applications is still very young. Only after changing the perspective from a more human-like robot towards an attempt to duplicate merely brain part and learning capability, the researcher could present robust solutions. Presented research has no attempt to replace the workers on a shop-floor; on the contrary, a solution for the support of them in daily operations is presented. Of course, the planning process should be transformed from highly repetitive routine calculations in Excel-sheets towards autonomous Real-Time Digital Twin of Assembly, which inevitably leads to a restructuring of the planning department. Still, gained value over the whole Supply Chain leave no doubt in the meaningfulness of such change.

In summary, this research provides insights on how the AI-based digital solutions within the supply chain can allow it to become more adaptive and thus, robust to the changes, which can be used by both researchers and company executives.

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