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Data-Driven Production Logistics – An Industrial Case Study on Potential and Challenges

Reference

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ABSTRACT

Production logistics is typically considered a nonvalue-adding activity with a low level of automation and digitalization. However, recent advancements in technology infrastructure for capturing real-time data are key enablers of smart production logistics and are expected to empower companies to adopt data-driven strategies for more responsive, efficient, and sustainable intrasite logistic systems. Still, empirical evidence is lacking on potential and challenges in industrial transitions toward such systems. The objective of this article is to analyze the potential and challenges of adopting data-driven production logistics based on an industrial case study at an international manufacturing company in the pharmaceutical industry. The industrial application is analyzed in relation to established frameworks for data-driven manufacturing, and key technology infrastructures are identified. The potential of adopting a data-driven solution for the industrial case is quantified through simulating a future scenario and relating the results to the five SCOR performance attributes: reliability, responsiveness, agility, cost, and asset management efficiency. The findings show that deploying a data-driven approach can improve the overall performance of the system. The improvements especially concern lead-time, utilization of resources and space, streamlining logistics processes, and synchronization between production and logistics. On the other hand, challenges in adopting this data-driven strategy include a lack of relevant competence, difficulties of creating technological infrastructure and indistinct vision, and issues with integrity. Key contributions of the article include the analysis of a real industrial case for identification of potential and challenges while adopting a smart and data-driven production logistics.

Keywords

data-driven, production logistics, smart, digitalization, transition, simulation

Introduction

Production logistics is often considered as a nonvalue-adding activity with poor access to timely and accurate data. Additionally, the constant increase in the variety of products because of market demand puts an extra pressure on production logistics systems.[1] Recently discussed concepts such as Industry 4.0 and smart manufacturing have shown great potential to deal with the aforementioned dilemma for production logistics systems.[2] Smart production logistics is here used as a term for a fully integrated, collaborative intrasite logistics system that responds in real time to meet changing demands and conditions in the factory, in the supply network, or in customer needs, in analogy with the definition of smart manufacturing as stated by NIST.[3]

One of the key elements to transform into smart production logistics is effective utilization of data, which is the major enabler for increasing the competitiveness for production logistics systems.[4] Even though most of the efforts have been related to overcoming technological challenges within smart manufacturing, it should be emphasized that data play a significant role in performing the transformation.[5] According to Yin and Kaynak,[6] the data produced within manufacturing have reached 1,000 EB, and this number is continuously growing. Considering the large amount of data available from manufacturing and logistical activities, it is possible to use this big data to extract valuable knowledge and constantly support and boost production logistics systems.[7] Therefore, data-driven manufacturing systems will have competitive advantages over their competitors,[7] higher levels of sustainability,[8] increased visibility across the supply chain,[9] and improved preventive maintenance.[10] It should be noted that authors consider any kind of smart manufacturing system as data-driven.[4] This assumption implies that all studies concerning smart manufacturing are relevant to this research.

A transition toward data-driven production logistics requires a clear understanding of outlook, potential benefits, and challenges. Furthermore, it is vital to know existing frameworks that support this transition. Because these large changes of real production logistics systems include substantial efforts and often take a very long time, the available empirical evidence regarding implementing data-driven frameworks and technologies is limited. The main objective of this study was therefore to evaluate the consequences of a transition toward data-driven production logistics and implementing data-driven frameworks and technologies, through analyzing the production logistics system of an international pharmaceutical manufacturing company. The overall research enquiry for this study was formulated as: What are the potential benefits and challenges of a transition toward data-driven production logistics in terms of reliability, responsiveness, agility, cost, and asset management efficiency?

In addition to the study of the industrial case, related data-driven manufacturing and logistics frameworks have been reviewed. As a result, the current situation was analyzed, and a future data-driven scenario was mapped based on the proposed scenario in literature. In order to compare the as-is with the to-be situation, a discrete event simulation software, ExtendSim, was used.

The simulation and the comparison of different key performance indicators prove that some of the characteristics of data-driven production logistics can be achieved, such as improved synchronization between logistic and production lines, shortened lead-time, better utilization of resources and space, as well as streamlining the logistics processes.

Method

The research is based on a single case study that was carried out in the largest manufacturing sites within one of the largest pharmaceutical manufacturers in Europe. The company is active within pharmaceutical and biopharmaceutical production and has almost 61,100 employees in 18 production sites. It supplies over 100 different markets. The study has been conducted in 1 of the 18 production sites at which over 30 different pharmaceuticals are manufactured.

RESEARCH APPROACH

In order to address the research question, an empirical single case study was selected as the methodological approach for this research. The case study method facilitated an in-depth understanding of potential benefits and challenges of the transition toward data-driven production logistics.[11] According to Meredith,[12] a case study can be considered as an appropriate method when the amount of unknown knowledge is considerable. Because the number of empirical studies regarding transition toward data-driven production logistics are limited, a case study was concluded to be an appropriate method.

CASE SELECTION

The basis for the case selection was the company's ambitious "one-touch vision" concerning their production logistics while having a complex and well-established production logistics system. In addition, the case company has strong collaboration with research centers, and this enabled empirical access including the collection of data, interviews of experts, and observations of the production logistics activities. The studied production plant is the launch site for new pharmaceuticals within the company and has a history of implementing lean philosophy for more than a decade; consequently, the production logistics system of the company has shifted to be aligned with lean principles. Quality in both product and process within the whole supply chain has high importance for the company, and there are many ongoing routines and planned projects to maintain and increase the quality level. In this effort, the company has announced that production logistics should reach "one-touch" as a vision. This refers to the number of times an item is touched when transported from goods receiving until the item is shipped to customers. In the current situation, each item is touched 20 times, on average. The results of the analysis showed that the case company has low information transparency within its internal logistical processes, and some of the logistical decisions made have low or no dependency on real-time data. They identified opportunities to improve efficiency and responsiveness by increasing the level of data exchange automation as well as benefit from data-driven approaches.

APPLIED METHODS FOR DATA COLLECTION

In order to be able to meet the explorative goal of this study, the production logistic process in the transition hall, delivery to the production lines, and waste handling are selected. Goods receiving, transportation to production lines, temporary storage of incoming material, and waste handling are the main activities in this process. The main objective of this study was to evaluate the consequences of a transition toward data-driven production logistics, and the following three questions were of main concern:

- What are the potential benefits of data-driven frameworks for production logistics systems?
- What are the challenges that the companies face in introducing data-driven smart concepts?
- What are the consequences of introducing technologies that enable data-driven production logistics?

As a starting point, we therefore examined existing literature, carrying out a search on SCOPUS using the key words ("data driven" or "smart" or "big data") AND "case study" AND ("logistics" or "material movement" or "material handling" or "warehous*"). The selection of the key word 'case study' was of specific relevance because we were interested in understanding the challenges and possible impact of already implemented data-driven smart production solutions. The search is focused on title, abstract, and keywords. The result is limited to the latest publication from 2015 until 2020. Besides, in order to filter irrelevant hits, the search is limited to the following areas: computer science, engineering, decision-making, business, management and accounting, and social science. Scopus database returned 210 hits. After reviewing the title and abstract, those publications that were relevant were reviewed in more details. The outcome was 11 articles who referred to and delivered results based on case studies. However, the case studies did not deliver sufficient information on the specific challenges the companies are facing when implementing data-driven smart solutions.

The second question required a qualitative analysis through closer investigation of the current situation at the plant. This was conducted by several factory visits, which were partly carried out within the project 'DIGILOG'[13] and partly as a practical case study for undergraduate students at KTH University. In addition, two logistics experts and two managers were interviewed. Data regarding production logistics flow were collected through direct observation and archive study.

The third question required a quantitative analysis of comparing the current state and an anticipated future state. This was collected and described in a simulation model developed by means of ExtendSim, comparing the current and future state of the unit of analysis. The model was developed based on the collected data from factory visits, archive study, and mainly interviews. To ensure the model validity, the results were discussed with one logistic expert and one logistic manger, and compared with existing historical data. Because not all the required data existed to create the model, some parts of the model are developed based on estimations. The outputs from the simulations were quantified in terms of key performance indicators.

The empirical data collection for questions two and three took about three weeks and included a factory visit, an interview, document review, and several follow up interviews during the simulation process (for question three). The data collection had an iterative process, which involved constant documentation and consultancy with production logistics experts in the factory.

APPLIED METHODS FOR DATA ANALYSIS

The current situation was explained and analyzed based on the collected data from factory visits, student projects, interviews, and meeting with managers that clarified the company's vision from a logistics perspective.

The future data-driven scenario is mapped based on the framework for data-driven manufacturing proposed by Tao et al.[7] Among all the reviewed frameworks, Tao et al.[7] have covered the data management process in a broader scope with more attention to the applications, characteristics, and potentials. Additionally, because the framework has been designed on a high level, it provides the possibility of interpreting the framework from an internal logistics perspective. Other frameworks have paid attention to data processing steps and data mining processes at a detailed level, which is somewhat outside the scope of this research. That is the reason authors have decided to choose the framework proposed by Tao et al.[7] for further analysis.

To be able to compare the as-is situation against the future scenario, the production logistics process is simulated and both scenarios are deployed. The outputs from the simulation models were clustered to the five performance attributes defined by the Supply Chain Operations Reference Model[14]: reliability, responsiveness, agility, cost, and asset management efficiency. Reliability, responsiveness, and agility are considered to be customer focused. Cost and asset management efficiency are considered to be internal focused. All SCOR metrics are grouped within one of the performance attributes. The model simulated one month of production in three working shifts and with a total number of seven operators. To avoid complication, the flow of shipping finished products to customers is not considered in this study. This is the reason why the number of operators in the simulation model is almost half of the operators in reality, which is 15.

Theoretical Background

Most of the existing frameworks are more focused on the overall picture of manufacturing, and production logistics is one part of this holistic view. According to Tao et al.[7] and Zhang et al.,[15] data lifecycle starts with data source, which can be collected from the entire value chain from design to recycle. The produced data can be collected in different ways and by means of different technologies but mainly through Internet of Things (IoT) technologies. Examples are using radio frequency identification (RFID) for flexible identification of items and sensor networks to monitor parameters such as temperature, presence, speed, etc. Historical data that exist in common manufacturing systems such as enterprise resource planning (ERP) and manufacturing execution system are another type of data that can be collected.[15]

In the next step, the large amount of collected data needs to be stored, and technologies such as cloud services enable reliable and flexible storage of data. To make use of collected and stored data, data need to be processed to create information and knowledge. This step requires special attention to data cleaning and removing duplicates and conflicting data. There are some supporting techniques like machine learning that provide benefits in addition to those from data mining methods.[10] In the next step, the clean consistent data need to be communicated. In cases where the user is a human, data need to be presented in a more explicit manner. Real-time data can be constantly visualized on smart devices.[6,10]

In the application step, the data can be used in different aspects of the system including data sources that have produced the data in the first place. As a result, the system is more agile and can adjust its behavior according to real-time flow of information.[7]

EXISTING FRAMEWORKS FOR DATA-DRIVEN MANUFACTURING AND LOGISTICS

Tao et al.[7] have proposed a theoretical framework that supports smart manufacturing from a big data perspective. The framework consists of four modules. The manufacturing module includes physical items such as materials, human resources, machines, etc., and the physical items in this module can be considered as the source of data.

The data driver module enables smart manufacturing by providing the driving force throughout the whole lifecycle of manufacturing data. This module receives data from the manufacturing module by means of cloud services and provides power for real-time monitoring and problems processing modules. The processed data in this module flows back to the manufacturing module in the form of explicit information and actionable information. **Figure 1** shows the framework in more detail.

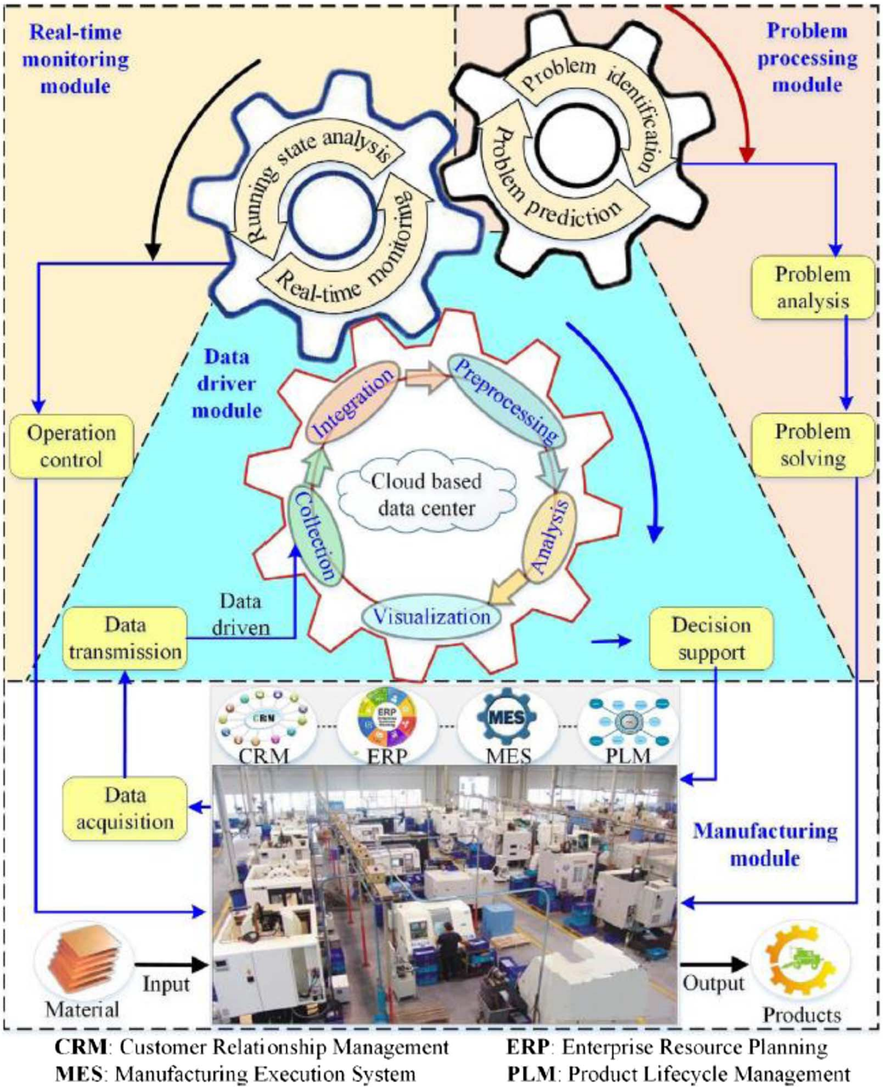
The real-time monitoring module receives data, which have been transmitted through the manufacturing module, and enables real-time monitoring of manufacturing. The ultimate goal of this module is to ensure quality despite changes and unexpected events. The problem processing module enables detection of problems in manufacturing. Additionally, it helps by suggesting feasible actions, root cause analysis, and analyzing potential impact on other parts of the manufacturing system. Real-time information and historical data help decision-makers and intelligent systems to address both current and upcoming issues.

Another framework suggested by Zhang et al.[15] is a methodical approach that aims to enable smart production line. Data self-perception is the first step within this method and is similar to the previous framework; data are collected automatically from a physical source of data such as a facility, an employee, products, etc. The examples for the enabling technologies are RFID, sensors, and wired and wireless networks. In the second step, the raw data collected earlier turn into meaningful information and knowledge necessary for decision-making. Real-time data from production, historical data, and simulation production data can be used at this stage to support physical and relational modeling. In the third step, the prepared data will be used to increase the understanding of the production line as well as to create predictive models. By comparing the perceived data with predictive models, any abnormalities will be figured out. Necessary instruction for the smart production line will be provided at the last step.

Zhang et al.[16] have proposed a three-layer framework for smart production logistics systems, namely intelligent modeling, smart production logistics, and self-organizing configuration. Similar to previous frameworks, physical objects equipped with IoT technologies are the starting point to acquire data. These smart objects can communicate in real-time and actively respond to changes happening in the logistics and manufacturing environment. In the second layer, smart entities can request for a manufacturing or logistics service and respond actively. Real-time logistics or manufacturing tasks are published by smart machines and smart material handling systems. Cloud computing has a necessary role in this layer because it enables the encapsulation of smart logistics services. The last layer actively organizes the relationship between logistics and manufacturing tasks. For example, when a manufacturing task is finished, a logistics task will be published by the machine on the cloud and can be allocated to the nearest logistics provider. On the other side, the manufacturing tasks can be triggered when a new material has been transported to a machine station.

Ren et al.[17] have proposed a framework for shop floor material delivery based on real-time manufacturing big data. Data collected from physical objects in the shop floor by means of sensing devices like RFID and smart sensors. To transmit the collected data, networking technologies WLAN and IPv6 are used as enabling technologies. The collected and transmitted big data will be preprocessed and stored by means of available middleware. To reach reliable data, cleaning, integration, reduction, and transformation must be done properly. The preprocessed and stored data will be used for data mining and application. Examples of applications are quality control, cost control, supplier selection, and shop floor dynamic scheduling.

FIG. 1 The framework of data-driven smart manufacturing by Tao et al.[7]



CHARACTERISTICS OF DATA-DRIVEN MANUFACTURING AND LOGISTICS

Data-driven manufacturing and logistics have some characteristics that describe the behavior of these systems. Tao et al.[7] have explained these characteristics as self-learning by utilizing historical and real-time data to perform preventive maintenance and quality control; self-regulating by utilizing real-time collected from manufacturing to constantly adjust to the new situation; self-execution by exploiting data captured from manufacturing processes to perform tasks with no human involvement; self-organization ability to adopt to new situations for optimal planning and scheduling; and customer-centric product development by analyzing customer needs for tailor-made products. Gröger et al.[18] discussed the enabling capabilities of data-driven manufacturing and logistics systems as these systems enable agile manufacturing by utilizing big data to optimize activities proactively; enable learning manufacturing by utilizing big data to create knowledge continuously; and enable human-centricity by utilizing big data to constantly supply context-aware information to human resources aiming to make data-driven decision-making. Zhang et al.[15] mentioned the effects data-driven systems have on manufacturing as guiding actual manufacturing by utilizing the vast scope of interactive data; in-depth data analysis to support data-driven decision-making; and instant feedback and control over the manufacturing system through real-time data circulation.

APPLICATIONS AND POTENTIAL BENEFITS FOR PRODUCTION LOGISTICS

Following categorization of data-driven application is inspired from Tao et al.[7]

Material Handling and Tracking

One of the primary goals of any logistics system is to deliver the right material at the right time to the right place. To meet this goal, different types of data including inventory data, location and positioning data, as well as progression data are required.[19] Material data combined with other sources of data, such as fleet systems, human resources, and machines, in order to have smooth material flow.[7] Material identification, quality, delivery time, and transportation method are some of the examples of required data for effective production logistics flow.[7] One example can be correct dispatching of material based on the availability of downstream activities. Strandhagen et al.[20] and Hohmann and Posslet[21] mentioned automated parts identification as one of the old technologies that can fit very well into the framework of data-driven manufacturing.

In addition, traceability plays an important role to ensure successful transition toward a data-driven system.[22] This is especially important for materials that have more strict transportation conditions to make sure material transportation complies with these regulations.[22] Increasing traceability will facilitate material distribution through real-time monitoring of the location of moving items as well as logistics equipment.[1] Hohmann and Posselt[21] have mentioned monitoring of internal transportation, which is achievable only through sharing data through a central platform for all the involved players.

Using autoidentification technologies such as RFID helps to realize the data-driven production logistics. It will free the registration from errors because manual mistakes are removed. This, in combination with other automated solutions such as robots, will facilitate a smooth picking process because the robot receives the identification process from autoidentification and historical data such as storage positions from a warehouse management system or ERP and performs the picking.[21]

Smart Scheduling and Planning

Proper production logistics planning and scheduling is necessary to utilize existing resources in an optimal manner. Different types of data like customer order, manufacturing status, manufacturing capacity, logistics resources, and equipment availability are required to perform smart planning and scheduling.[23] This information facilitates rapid resource availability and real-time monitoring of inventory levels[24] to make optimal planning for material ordering, material transportation, and route planning.[25] According to Hofmann and Rüsch,[1] by increasing the traceability of products, real-time data regarding consumption point, inventory level, and parts identification will be shared with other stakeholders; consequently, the need for deterministic material planning will be minimized. Intelligent optimization algorithms can use the big data collected from the shop floor combined with historical data from existing systems such as ERP to realize optimal data-driven planning.[24] Earlier preparation of the goods receiving process is an example of using data-driven approaches that can reduce the process time. In addition, real-time information of the incoming goods connected to external logistics facilitate the planning and flexible scheduling.[21]

Smart Logistics Equipment Maintenance

According to O'Donovan et al.,[10] maintenance costs can be more than 30 % of the whole operating cost. Data analytics has the ability to predict the failure of machines and equipment. The data provided by sensors attached to equipment in addition to historical data can be used to predict the failure tendency of equipment.[26] By deploying smart devices and sensors, real-time data can be combined with historical failure data to predict the possible failure time.[27] This is possible to be realized through big data analytics.[7] Additionally, energy consumption is an important indicator of probable failure, and it is possible to capture this through analyzing the multidimensional energy consumption model.[7]

Table 1 helps to find a more detailed picture of the potential benefits that have been studied by other researchers. The table shows case studies that benefit from implementing data-driven approaches and enabling technologies.

CHALLENGES IN THE TRANSITION TOWARD DATA-DRIVEN PRODUCTION LOGISTICS

As discussed earlier, data-driven production logistics is part of the fourth industrial revolution; it is logical to argue that many of the challenges mentioned for Industry 4.0 and smart manufacturing are true for data-driven production logistics as well. According to Ribeiro and Björkman,[28] there have been some similar efforts in academia such as holonic manufacturing systems, bionic manufacturing systems (and more generally, multiagent systems), and service-oriented architectures that somehow experienced similar challenges. In general, these challenges are represented in two main categories: strategic and organizational challenges.

Strategic and Organizational Challenges

According to Strandhagen et al.,[20] one of the challenges to implementing Industry 4.0 technologies is the lack of a road map, even though it is not possible to have a unique road map that fits all industries. Hofmann and Rüsch[1] mentioned some serious challenges for implementation of Industry 4.0 components. The value creation process will considerably change, and this will remove and replace some of the conventional organizational boundaries. This will force organizations to prepare appropriate infrastructures, review guidelines and standards, increase data security, and expand competence.[1] Ribeiro and Björkman[28] have mentioned the limitations in the process of validation and verification as a challenge for transition toward a data-driven system that is mainly rooted in the readiness of organizations to embrace the upcoming industrial revolution.

Hohmann and Posselt[21] asked the question whether companies avoid embracing data-driven approaches, such as the implementation of cyber-physical systems (CPSs), in a wider scope because they feel they need to learn more about these changes in controlled environments such as test beds or because they have limited capacity to exploit the potentials of these approaches.

Big Data and Information Management Challenge

Hohmann and Posselt[21] argue that information has the central role for any CPS. Because many different actors need the information to make optimal decisions, it will be a challenge for any production logistics system to manage the information flow. In such a system, the data producer and consumer can be the same entity, and the existence of a central data exchange platform is inevitable.[21] This platform should facilitate the flexible replacement of old data sources and the addition of new ones.[29]

On the other hand, assigning duties within the production logistics systems to the right actor is a challenge. This can be challenging from an information management perspective when the number of actors and the complexity of logistical tasks increase over time.[21] According to Rehman, Hark, and Gruhn,[30] there are several challenges for big data for CPS including real-time, infrastructure, data quality, and security. Real-time refers to the ability of the system to collect and process the data within a very short amount of time. This time constraint creates challenges for the system because many different parts within the CPS system should collect and process data in real-time.[30]

Successful implementation of CPS requires effective handling of big data. To do so, an appropriate communication infrastructure is needed that facilitates the integration of big data into CPS. Lack of appropriate architecture that can facilitate the development from the conceptual level to the physical implementation level is also considers to be a challenge.[28]

In a data-driven system, decisions are made based on the provided data. From this perspective, the quality of data that has no duplicates, unreliable data, noises, etc. is important. In this respect, in addition to choosing appropriate transferring protocols, even choosing the right type of hardware, such as sensors, has an effect on data quality.[30]

Security and privacy have notably high importance for any data-driven system because no unauthorized access should be possible. This implies that the system should meet the objectives of security including authentication, integrity, availability, and nonrepudiation.[30]

TABLE 1
Related case studies and their applications in production logistics

Case Studies	Application in Production Logistics
1. Fernández-Caramés et al.[39] proposed a system that has been tested in a warehouse, and the results depict a high ability to collect inventory data faster than a human operator. In addition, the system is able to locate items in the warehouse in an efficient manner.	a. Material handling and tracking
2. Wilkesmann and Wilkesmann[40] have discussed how Industry 4.0 can organize innovation and routines within organizations. They improved the material flow within a 1,000-m^2 research hall by using 50 AGVs. All the transportation was handled autonomously with no human intervention. In addition, augmented reality technology was used to allow hands-free picking in the warehouse. The results show reduction in the number of faulty picking.	a. Material handling and tracking
3. Pang et al.[41] have presented a software service that facilitates order picking from a supply hub to the manufacturer. The proposed software enabled data-driven transportation management service by using autoidentification technologies to coordinate the fleet in real time. The implementation results show that planning and scheduling time have decreased by more than 40 %. Resource visibility has significantly increased, and the average cycle time has decreased by 11 %.	a. Material handling and trackingb. Smart scheduling and planning
4. Ehm[42] proposed a data-driven method to solve the problem of integrated disassembly process planning and scheduling. Solving the model for a representative daily set of 24 disassembly jobs showed an improvement of 18 % upon the conventional scheduling approach.	b. Smart scheduling and planning
5. Zhang et al.[16] have proposed a conceptual data-driven framework for smart production logistics systems. The framework facilitates self-organizing configuration mechanisms. Within their case study, the total manufacturing cost of the separated production logistics was around 22 % less than the total manufacturing cost of smart production logistics system. The proposed method reduced the total manufacturing time by around 51 % and the total energy consumption reduced by around 37 %.	a. Material handling and trackingb. Smart scheduling and planning
6. Wang, Zhang, and Zhong[43] proposed a proactive data-driven material handling method for CPS-enabled shop floor. RFID technologies and advanced information and communication technologies were implemented so the production fluctuations could be tracked in real-time. Within the case study, it was found out that the proactive material handling method can largely reduce the total energy consumption (52.7 %) and distance of trolleys (66.7 %) simultaneously. By using intelligent-adaptive assistance systems, it is possible to perform onsite maintenance by the operators through the guide, which is provided by the assistance system.	a. Material handling and trackingb. Smart scheduling and planningc. Smart logistics equipment maintenance
7. Wan et al.[44] have introduced a cognitive industrial entity called context-aware cloud robotics. The aim was to improve advanced material handling. The architecture of the proposed entity is based on the data collects from the shop floor. RFID, cloud computing, and wireless communication were the major enabling technologies. A simulation within a case study has been performed, and the results show that the proposed method reduced energy consumption and helped to have better utilization of AGVs in the case study. In addition, it has facilitated forecasting predictive and proactive maintenance schedules.	b. Smart scheduling and planningc. Smart logistics equipment maintenance
8. La Scalia et al.[45] proposed a system to monitor and control the supply chain of perishable products. The proposed model collects data from the shelfs in real-time and shares the data with different stakeholders in order to facilitate better planning on supply chain. Tracking and sensing technologies were used to measure and control parameters like temperature, humidity, carbon dioxide level, etc. The proposed model can help to provide better planning on the supply chain of perishable products.	a. Material handling and trackingb. Smart scheduling and planning
9. Ma, Nie, and Lu[46] have combined big data, mobile internet, and the supply chain effectively and pointed out the competitive advantages created by big data and mobile internet.	a. Material handling and tracking

TABLE 1 *Continued*

Case Studies	Application in Production Logistics
10. Zhong et al.[19] discussed a new approach that can support decision-making by visualizing the RFID- enabled shop floor logistics Big Data in Cloud Manufacturing. The results of the case study revealed that using this data-driven method helped the decision-makers to evaluate the performance of logistics personnel as well as to analyze the detailed costs for transportation of each of the products. In addition, they could show that using a data-driven technology can help to estimate the delivery time and analyze operators performance.	b. Smart scheduling and planning
11. De Felice, Petrillo, and Zaomparelli[47] have described a method to digitalize warehouse operation within a case study. The analyzed technologies are based on CPS and data-driven technologies such as RFID and smart warehouse. The main results were analyzed through Flexsim 2017 software. The results show that the processing time for the reception of the purchased component decreased by 41 %. In addition, the project could save 10,600 USD/day. In addition, real-time management of the processes became possible through real-time data transition across the company sectors.	a. Material handling and tracking

Note: AGV = automated guided vehicle; CPS = cyber-physical system.

TECHNOLOGIES FOR DATA-DRIVEN MANUFACTURING AND LOGISTICS

According to Cooper and Wachter,[31] it is difficult to conclude that there is one specific list of technologies that can be implemented for all systems. It is mainly because each system has its own specific context and requirements. However, some technologies are highlighted by researchers. Hohmann and Posselt[21] have divided the enabling technologies for data-driven manufacturing and logistics into four main categories based on their functionality.

- Data acquisition: Wi-Fi, Bluetooth, Barcode, RFID, QR-code, near-field communication, and smart sensors;
- Data communication: Wi-Fi, Bluetooth, wireless sensor networks, internet, and cloud computing;
- Data processing: cloud computing, embedded processors, data analytics, and data mining; and
- Data visualization: virtual reality, augmented reality, and simulation software.

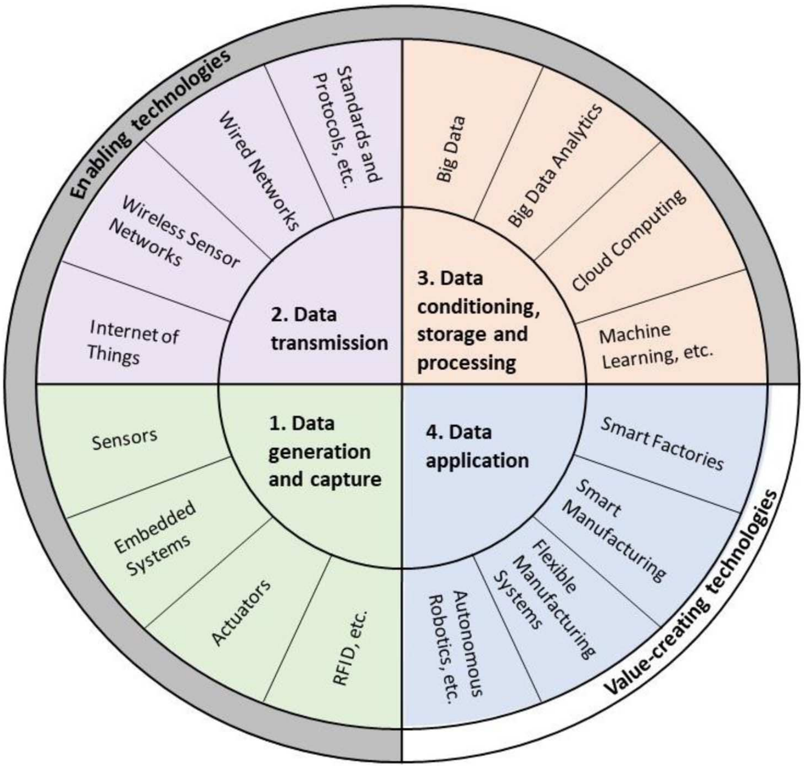
Klingenberg, Borges, and Antunes[4] have done a systematic research review to find out Industry 4.0 enabling technologies. Among 111 articles, 5 technologies were mentioned more frequently by researchers including CPSs, IoT, big data, big data analytics, and cloud computing. Based on their argument, technologies in this area can be divided into enabling and value-creating technologies. Enabling technologies are necessary for creating the infrastructure that is needed for data-driven manufacturing systems, but they are not sufficient for moving toward a CPS vision. These technologies have the function to collect, transmit, condition, store, and process data, where examples are RFID, sensor networks, machine learning, cloud computing, and big data analytics. Value-creating technologies have the function of applying the data provided by enabling technologies,[4] such as smart factories, smart manufacturing, autonomous vehicles, and smart robots. **Figure 2** shows more details.

USE OF SIMULATION FOR DATA-DRIVEN PRODUCTION LOGISTICS

In general, manufacturing simulation has been used in order to compare and analyze various possible scenarios within manufacturing systems to support the decision-making process. McLean and Shao[32] studied different kinds of manufacturing simulation applications. Song, Wang, and AbouRizk[33] proposed a system for modeling virtual factory for industrial fabrication shops. They have introduced the process of collecting factory data in a systematic way in addition to discussing the use cases of virtual factory.

Recently, with the emergence of the concept of smart manufacturing system and the fourth industrial revolution, the role of simulation in Industry 4.0 has become an interesting subject for researchers. This research is mainly concerned with the application and utilization of manufacturing simulations from different perspectives.[34]

FIG. 2
Enabling and value-creating technologies inspired by NIST.[3]



In the field of production logistics, Filz et al.[35] applied simulation as a method for analyzing the behavior of the existing production logistics system.[35] In their study, manufacturing simulation was used to analyze the complex production logistics behavior of a flexible production system.

Many researches in simulation-based optimization have been conducted mainly on production systems. However, as the logistics of the production system becomes more complex, some research considering production logistics has also been conducted.[36] Although many manufacturing simulation studies are well established in theory, the number of practical applications is rather low. Sobottka et al.[37] introduced a method for optimizing simulation-based production logistics planning for the food industry.

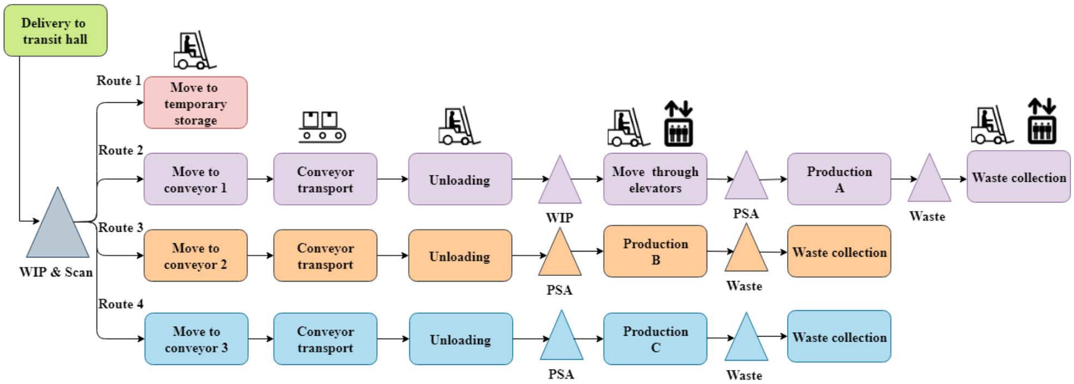
Through what-if simulation, the results according to scenarios or input information can be analyzed quantitatively. Accurate input information helps to improve the quality of the simulation results. Mieth, Meyer, and Henke[38] proposed a framework to utilize real-time data in manufacturing simulation. This framework contributes to better quality in manufacturing simulation. The next section will focus on as-is analysis, which provides the baseline for the simulation of the future data-driven scenario.

Empirical Findings

AS-IS ANALYSIS

One of the main production facilities is located in Sweden, including two sites. Site 1 orders and receives items that are needed for production from site 2 and sends finished products for final delivery to the customers. Site 1 includes a production facility that spans several floors and has storage for semifinished products, cold chain, and 'fixed bin' storage. Today, the production units in site 1 order materials through an ERP system. Incoming pallets from site 2 are received by site 1 in an area called the transition hall. A total of 15 operators work in 3 shifts, which

FIG 3. Production logistics flow at the transition hall-delivery to production lines.



means there are 5 operators per shift. One to two operators are busy with waste handling, and three to four operators are busy with pallet transportation.

Logistics personnel unload the materials from trucks by means of lift-trucks and place them on a scanning area. At this stage, an operator scans the pallets to update the ERP system. Depending on the items, pallets are divided into four different routes. For the first route, pallets will be stored in a temporary storage for later use after 72 h, shown in figure 3. The second route is dedicated to production line 'A'. Scanned pallets will be moved by lift-trucks to a conveyor belt that has the capacity to carry 12 pallets simultaneously. Within the production line A, another operator receives the pallets and transports them through elevators to different floors depending on the specific destination of the received item. Pallets will be stored in a temporary area called the production storage area (PSA). The production personnel will fetch the items from PSA even though they do not know the exact arrival time and the address. The third and fourth routes are used to transport items that are needed for production lines 'B' or 'C'. Similar to line A, pallets are loaded to a conveyor belt with a capacity of 10 and 4 pallets for line B and line C, respectively. After reaching the production area, pallets are unloaded from the conveyor and delivered to PSA for line B or C.

Within each production line, there are some waste bins that need to be collected when the capacity is full. For production A, wastes need to be collected and transported back to the sorting stations through elevators by means of lift-trucks. Other production lines only need the lift-trucks. In general, 30 % of the production logistics activities are used for waste handling.

Items that are needed for production line B will be transported through the third route. Similar to the second route, parts will be transferred through a conveyor belt with the capacity for 10 pallets to line B and unloaded from the conveyor by means of a lift-truck. The pallets will be moved to the PSA specified for line B.

Current Issues

Within the production logistics of the case company, data sharing is interrupted on several occasions and it has caused some issues. The following describes which activities deal with missing information (see fig. 4).

- Delivery from site 2 to transition hall
  The transition hall has no information regarding the quantity and identification of the incoming items. On some occasions, the number of incoming items is high; therefore, there is not enough area to receive the items and the logistics operators have to unload the items outside the transition hall. On the other hand, sometimes the trucks arrive empty.
- Loading the conveyors
  If the capacity of the conveyors becomes full, the operators have to unload the pallets next to the conveyor and reload the pallet on the conveyor when there is enough capacity. In such a case, the information regarding the capacity of the conveyors is not communicated to the operators.

- Transportation through elevators
  The information regarding the availability of elevators and arrival time is not available to the operators. Consequently, sometimes the operators have to wait for the elevators to be able to transport the pallets to the intended floor.
- Waste bins collection
  Operators have no information that tells them waste bins need to be collected. The status and place of waste bins are not communicated to the operators. In this case, the operators have to look around and search for waste bins that need to be collected.
- Delivery to PSA
  Production personnel receive no information regarding the arrival time and location of the ordered items. As a result, the pallets have to wait in the PSA for a long time. On the other hand, sometimes the production personnel have to check the arrival of the items several times.
- Scanning the pallet barcodes
  On some limited occasions, the barcodes of the pallets are in poor condition and the operators cannot scan the barcodes. In this case, pallet identification becomes challenging.

TO-BE SITUATION

In this section, besides mapping the future state, some of the enabling technologies will be introduced that have the potential to be used in the production logistics. For the future state, two scenarios are defined. The first scenario is intended to keep human workforce in the loop. Therefore, no human will be removed from his or her job. However, in the second scenario, truck drivers will be replaced by AGV. In both scenarios, the main objective is to automate the information flow regardless of the level of process automation.

Based on the framework discussed earlier, the following structure is suggested by authors to be used for the production logistics system regardless of the level of automation as illustrated in figure 5. As discussed earlier, the real-time data from the logistics module feeds the data-driven module where historical data from ERP can be used as a complement. Real-time monitoring module ensures that the production logistics system is under real-time monitoring and any changes in the system will be taken into account to support the system with data-driven decision-making.

On the other side, the problem-processing module can be used in order to predict any failure in the conveyor system, forklifts, and trucks. In the case of fully automated flow, trucks can be replaced by an autonomous AGV system, and the problem-processing module can be used to predict the maintenance status of the AGVs. Items within the logistics module communicate to the data driver module through real-time data flow. Data will be used

FIG. 4 Value stream map delivery to production and waste collection.

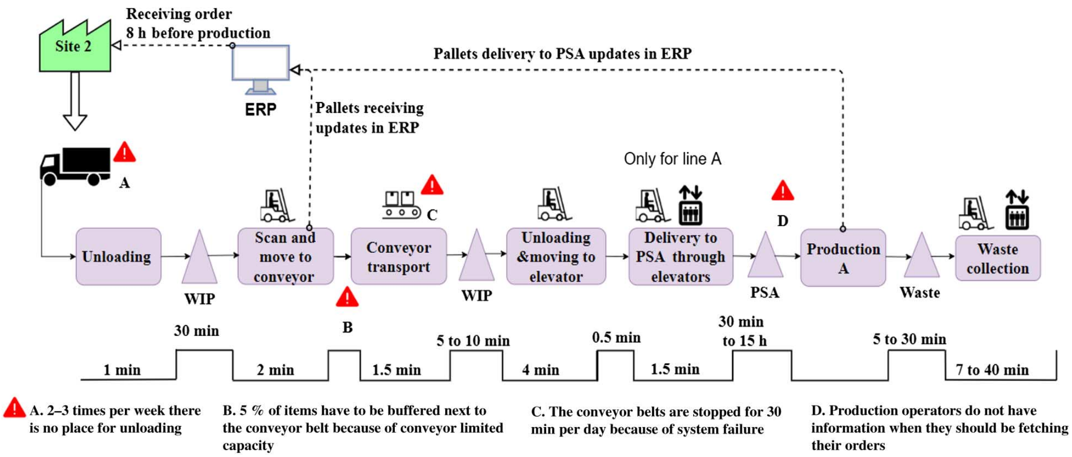


FIG. 5 Data-driven production logistics framework at the case company based on the framework proposed by Tao et al.[7]

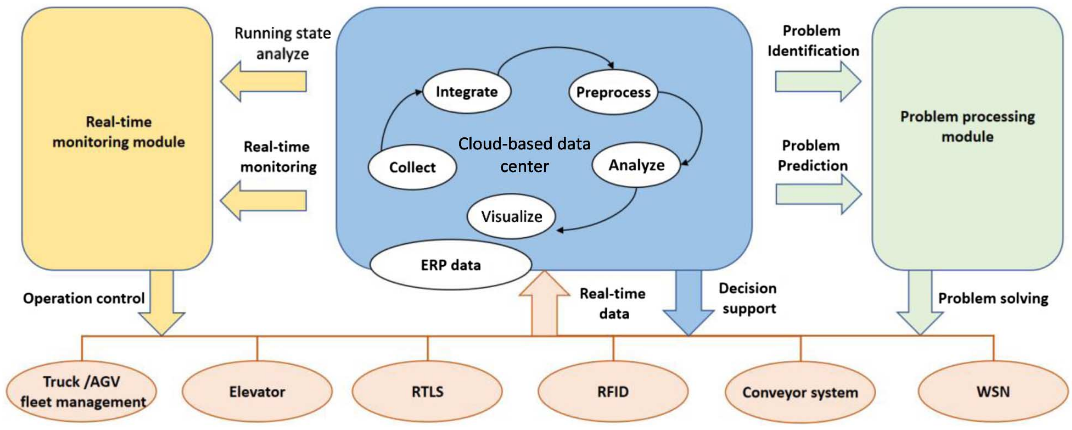
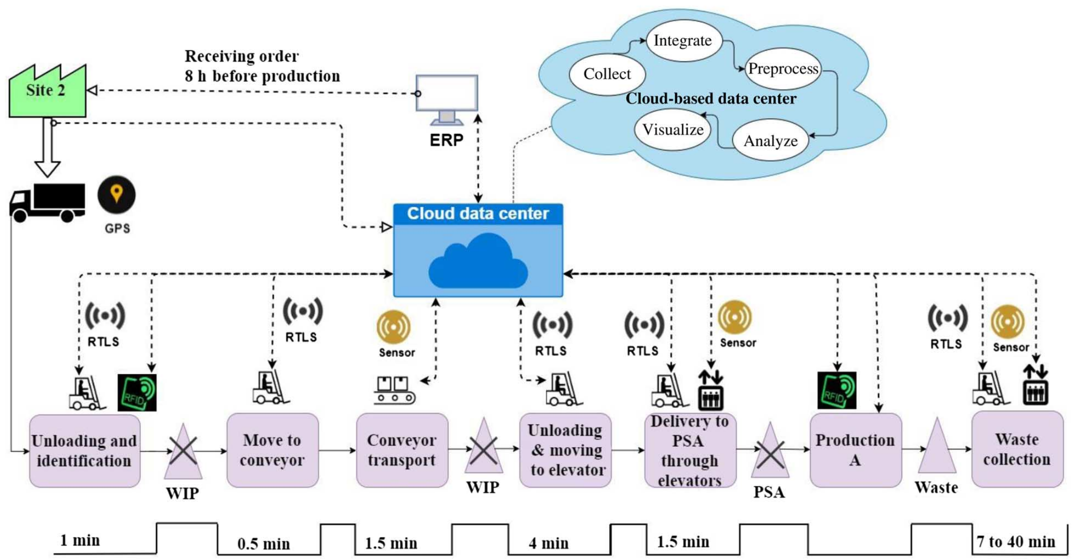


FIG. 6 Value stream map of the future scenario.



for visualization, decision making, and real-time monitoring. The real-time monitoring module will help to control the logistics operations by helping entities to communicate in real-time. For example, AGVs can communicate with conveyor belts in order to find the optimal timing for loading the conveyor with pallets.

As shown in figure 6, the incoming parts from site 2 will be traced in real-time in order to facilitate early preparation for goods receiving. Consequently, no items will be unloaded outside the goods receiving area. By using autoidentification technologies such as RFID, scanning of the pallets will be removed from the process.

In this case, the problem with unreadable barcodes will be solved. The identified parts will be registered in the ERP system, and information will be visible to other stakeholders such as production lines and customers of the items. All the data handling steps including collection, integration, processing, and analysis will occur by means of big-data analytics and cloud services. The conveyor systems will be equipped with smart sensors, and for collecting and transmitting the data, technologies such as wireless sensor networks will be used to transfer the data.

Artificial intelligence or machine learning techniques can be used to process the data. To optimize the use of computational power, cloud computing or fog computing technologies can be used. In case of using AGVs instead of the trucks, the AGV fleet management system will use real-time location and operational status of the AGVs to assign the most suitable AGV to perform the unloading. The RFID data, combined with the production ordering data recorded in the ERP system, will enable the AGV to receive the address to transport the pallet to the intended conveyor belt. The status of the conveyor belt will be transmitted to the cloud system, and the AGV fleet management can make optimal planning depending on the availability of the conveyor system.

After pallets are transported to the production area, the arrival of pallets will be communicated to the truck drivers or AGV fleet management system by means of sensors and wireless sensor networks. This will help to remove or at least reduce the queue length next to the conveyor system. In addition, the availability of elevators will be communicated to truck drivers or AGV system by means of IoT technologies. This will omit the waiting time for the truck drivers or AGVs. Arrival of the pallets to the PSA will be communicated in real-time with production operators who are responsible for fetching the pallets.

When the capacity of a waste bin is full, the information can be communicated with logistics operators or AGV fleet system. This can be done either manually or automatically. Production operators can make a service request in the existing system (uses to request transportation for finished parts), and the request will be communicated to the logistics operators. It can be done automatically by using sensors to detect the levels of waste bins and communicate it over IoT solutions to request transportation. This will also remove or reduce waiting time for waste bins as well as save time for logistic operators because there will be no need to move around and search for bins to collect. One of the most important requirement of the future scenario is the real-time status of logistic equipment like trucks or AGVs. The central unit of the system will process the data that is collected and delivered to the cloud by means of big data analytics to perform optimal job allocation to available resources. **Figure 6** depicts the value stream map of the production flow in the future scenario.

As can be seen in **figure 6**, there will be several sources of data available in the future state. The AGV fleet management system will produce and consume data regarding location operational data, time, maintenance status, and speed. These data will be used to streamline the unloading process from the trucks, material movement between scan zone and conveyers, material movement through the elevators, and material movement from the conveyors to the production lines.

The real-time location system (RTLS) will produce data regarding real-time location of items, and this can be used to increase the efficiency of material movement between scan zone and the conveyer system, material movement through the elevator, and material movement from the warehouse to the production area.

The RFID will produce items identification data, and it can be used to improve the truck unloading process and update the ERP system more efficiently.

Data regarding position, maintenance status, operational data, and availability status will be obtained from the elevator by means of sensor networks in order to facilitate communication with the AGV fleet management system or the operators. In addition, the sensor networks will provide operational status data and object detection data from the conveyor system. This will integrate the existing equipment into the surrounding environment.

SIMULATION OF THE FUTURE STATE

Because the number of unknown parameters was relatively high and the correlation among the parameters was not clear, it has been decided to simulate the production logistics process by means of ExtendSim. **Figure 7** shows a snapshot of the future-state simulation at the case company. All the activities have random processing time, which represents a real situation in the case company. **Table A1** and **A2** in the appendix show the AS-IS situation. **Table A3**, **A9** and **A10** provide more information about To-Be situation.

Simulation Results

In this section, the results of the simulation are presented based on SCOR attributes. In terms of reliability, which is the ability to perform tasks as expected with a focus on the predictability of the outcome of a process,[14] the case

FIG. 7 Simulation of the future scenario in ExtendSim.

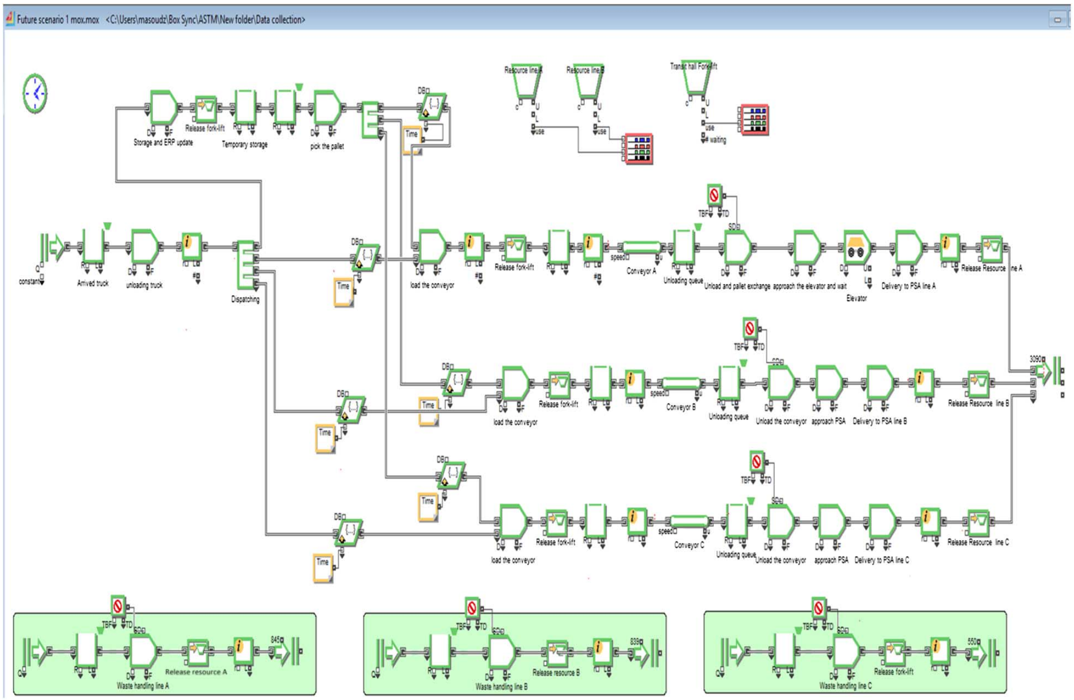


TABLE 2
Reliability of production logistics in current and future situations

Reliability	Current State	Future State
Orders delivered in full	100 %	100 %
Delivered on committed time	99 %	100 %
Delivered to the correct location	100 %	100 %
Waste bins collected in full	100 %	100 %
Waste bins delivered to the right sorting station	100 %	100 %
Wastes collected on time (average for 3 lines)	81.6 %	90 %

company has a high level of reliability of delivering right orders at the right time to the right location. From this perspective, the future scenario will not make any considerable improvement except for waste collection. Almost 19 % of the waste collection in today's situation happens with delay. After deploying the data-driven method, this number will be reduced to 10 %. Table 2 shows these parameters in more details compared to the current and future states.

In terms of responsiveness, which is the speed of performing tasks,[14] lead-time to deliver the pallets will significantly decrease for all the production lines from 106 to 35 min in average. Table 3 gives more details about this. Today, production lines have to make order at least 8 h prior to production. Within a lean environment, this will put pressure on production lines and decrease the flexibility degree. After transition to data-driven PL, this number can be reduced to only 2 h. It should be noted that this number includes the time requires for transporting parts from site 2 which is about 1 h. Today, pallets that are delivered to the PSA have to wait between 30 min to 15 h. Even though production lines have to order 8 h before it is actually needed, some place orders much earlier to secure the buffer they need. Besides, production line operators have no information regarding the exact delivery time. They have to guess when they should fetch the ordered parts, and in some cases, they have to check the PSA

TABLE 3
Responsiveness in current and future situations.

Responsiveness	Current State	Future State
Lead time for delivery to production	106 min	35 min
Planned time for delivery	8 h (1-h transport from site 2)	2 h
Waiting time in PSA	From 30 min to 15 h	15 min
Cycle time from unloading to dispatch to lines	34.5 min	19.12 min
Waiting time to pick wastes	6.07 min	2.26 min

area several times before the parts arrive. In the future scenario, this number will be reduced to 15 min, which is the maximum required time to fetch the delivered pallets. The simulation model and observation of the transition hall show that scanning the incoming pallets is a bottleneck. In the future scenario, the scanning will be replaced by autoidentification technology and consequently the cycle time will be reduced to 19 min. Waiting time to collect wastes will decrease to less than half from 6 to almost 2.5 min.

According to SCOR,[14] agility is the time needed for that system to respond to external influences such as market change. In this case, 20 % has been seen as a logical number for increasing market demand.[14] By increasing 20 % of incoming material to the transition hall, the lead-time will become more than 20 h, whereas in the future state, this time is less than 7 h. In case the production lines need to increase the delivery volume by 20 %, the lead-time in the current state is more than 2 h, whereas in the future state, this time will be less than 1.5 h (**Table 4**).

The cost attribute represents the cost of operating the logistical activities.[14] It should be noted that the cost of investment has not been considered in this research because of many unknown parameters that affect the final cost, including technology cost, infrastructure cost, consultancy cost, education cost, etc. Therefore, it is decided to compare the operators' utilization rates. As mentioned earlier, in the case of replacing trucks with AGVs, the number of operators will be reduced to three because they will have supervisory roles (**Table 5**).

Asset management refers to the ability to effectively use assets and includes inventory reduction. Metrics include inventory duration of supply and usage of space.[14] In the current situation, on average, each pallet waits in a queue for about 2.5 h. In the future state, this time will be reduced to almost 1 h and 45 min. As discussed earlier, in the future scenario, production operators will receive real-time information regarding the status of their orders. Consequently, less pallets need to be stored in PSA. Numbers shown in **Table 6** prove that area in use will be reduced from 20 to 5 m^2.

The unloading is the bottleneck of the process in the current situation. Because forklifts are sometimes busy with other tasks such as sorting pallets or delivery to production lines, they are not available to load the pallets on the conveyors. In that case, unloading time varies between 2 to 40 min. By communicating real-time status of arrived pallets, this time can be reduced to 5 min, which includes the travel time from the production line to the conveyor system and unloading activity. **Table A4**, **A5**, **A6** and **A7**, give more details.

TABLE 4
Agility in current and future situations after 20 % increase in raw material and delivery

Agility	Current State	Future State
Lead time after increasing 20 % raw material	1,244 min	393 min
Lead time after increasing 20 % delivery to production	138 min	80 min

TABLE 5
Operators' utilization in current and future situations

Cost	Current State	Future State 1 (Keeping Operators' Jobs)	Future State 2 (Replacing Truck Drivers with AGV)
Human resources utilization (average of transition hall and production line operators)	80 %	51 %	0 (2 operators will be removed)

TABLE 6
Asset management in the current and future scenarios

Asset Management	Current State	Future State (1)
Inventory time of supply (WIP)	152 min	103 min
Area in use for PSA	20 m^2	5 m^2

TRANSITION CHALLENGES

The interviewees have mentioned that the case company has some concerns regarding the reliability of data-driven enabling technologies. This is partly because of the newness of some of the technologies and partly because of the complexity of integrating different technologies to achieve effectivity on a system level. In addition, it is not so clear what the use cases and the application of each of the enabling technologies are. Because these technologies have not been used in the case company, there is no estimation regarding the investment that is needed to implement these technologies. It is not clear what types of competence are required to move toward a data-driven state. In the following, some of the transition challenges recognized during this study for the case study are discussed.

The production area is constructed in several floors, which makes it difficult to navigate AGVs through different floors. Because the building is of an older construction, aisles are rather narrow and it is challenging to manage all the traffic in the corridors. In addition, if the case company decides to replace the existing trucks with automated solutions such as AGVs, there will be a need to have plenty of AGV's working next to the existing equipment such as conveyor systems. This will not happen overnight, and the transition involves an effective cooperation among new technologies with older equipment. Controlling the traffic in the shop floor will be complicated because many different AGVs should be synchronized with the existing trucks. For example, it should be clear which vehicle in which situation has the priority for passing through.

Installation of many sensors with different types will be needed to facilitate the connectivity of logistics equipment. Integrating many sensors into the existing data management infrastructure can be a challenging task. A similar issue applies to the integration of other technologies such as RFID and RTLS.

The elevators have no possibility of being connected to wireless networks, thus it is difficult to collect data regarding position and operational status, and to communicate with the other entities and systems such as the AGV fleet management system or the operators. To deal with this problem, the case company needs to make a considerable investment to connect the elevators to the data exchange infrastructure.

In the case of implementing RFID technology, the case company has no clear plan for implementation. It is not clear who is responsible to attach the tags to each of the incoming pallets and how the tags should go back to the supplier for later use.

Real-time data collection is one of the key aspects of data-driven production logistics. This requires a stable and robust infrastructure that minimizes latency and facilitates data analysis. The case company also needs to consider the investment that is needed to develop this infrastructure and competence in different areas. The connectivity of data producers and consumers should be done in a flexible and robust manner. Today, within the case company, most of the communication among entities happens through one-to-one integration. This will not be a sufficient solution because the system will face many changes over time. It should be possible to add or remove data producers and consumers without considerable efforts and with no need to redefine the integration among the entities. Even tough concepts such as enterprise service bus, which is based on service-oriented architecture, have shown good potential to solve the integration issue, but the case company has limited experience on implementing such solutions.

Discussion and Conclusion

The research question guiding the research was "What are the potential benefits and challenges of a transition toward data-driven production logistics in terms of reliability, responsiveness, agility, cost, and asset management efficiency?" Building upon the results presented in the previous section, this discussion section is structured according to the three main aspects of the stated research question: the potential benefits, challenges, and consequences of a transition to a data-driven production logistics.

POTENTIALS OF DATA-DRIVEN FRAMEWORKS

According to Hofmann and Rüsch,[1] Industry 4.0 is a vague concept that implies different interpretations. Frameworks seem necessary to clarify the complexities of the related concepts such as data-driven production logistics. The potential for transition toward data-driven production logistics can be categorized into three.

- First, data-driven production logistics will increase the visibility in internal logistics through improved material handling and tracking. Real-time data captured from the physical environment, equipment, products, and resources will be combined with historical data to facilitate optimal material handling. Goods receiving, storing, and distribution will be supported by a constant flow of data including parts identification, destinations, real-time location of parts, resources and equipment, routes' status, and the operational and maintenance status of equipment. By automating the data-exchange process, errors caused by faulty data sharing will be removed from production logistics systems. Because data are analyzed from different perspectives, it is possible to have a holistic view over resource availability and resource utilization, systems' efficiency, and the equipment's maintenance status. Consequently, decision-making will be data-driven. The results from the simulation showed that material handling has improved in terms of shorter lead-time, shorter queue length, reduced space in use, and better utilization of resources.
- Secondly, real-time availability of customer orders, consumption point, inventory level, and resources availability will facilitate optimal order planning. Bullwhip effect will be reduced, and earlier preparation of goods receiving will be possible. Connectivity to external logistics increases flexibility in scheduling. The simulation results prove that the production lines can have more flexibility by ordering the required parts just 2 h before production instead of 8 h. Besides, the size of buffers will decrease, and the operators' time will be used more effectively because they do not need to search the PSA area frequently to fetch their orders.
- Third, the availability and efficiency of equipment will be increased through preventive maintenance. Real-time data regarding the performance of equipment including temperature, energy consumption, speed, vibration, etc. will be combined with historical data. The big data analytics provide knowledge to decision-makers to preform preventive maintenance. According to the simulation results, even though failure of the conveyor system did not show any significant effect on the outcome, knowing the probable breakdown time will help to reduce queue lengths before the conveyors.

CHALLENGES FOR A TRANSITION TO DATA-DRIVEN LOGISTICS

Some of the challenges were discussed earlier in more detail, including the difficulty of using AGV systems, old transportation infrastructures, need for developing information management systems, and investment in IT infrastructures. In general, the challenges can be categorized into two sections.

- Strategic and organizational challenges. The lack of a roadmap for stepwise implementation of data-driven production logistics is an issue mentioned by researchers. The results of interviews and document analysis proved that even though the case company is willing to improve the information flow and has defined one-touch as a vision, it is not so clear how this vision will be achieved. According to literature, the value creation process will significantly change the organizational structure and boundaries. Although the case company was aware of the changes, it was not so clear how these changes, including the finding and developing of right competences, reorganizations, etc., should be managed. Besides, a lack of knowledge and the complexity of issues like data-driven approaches create difficulties for opening up discussion on all of the organizational levels.
- Big data and information management challenge. According to the literature, building a central information management infrastructure is necessary for a data-driven production logistics system. Because all of the logistical activities will depend on the performance of this infrastructure, it should have extremely high reliability. Designing and maintaining such a system can be a challenge for organizations. Ensuring high

quality of data is another challenge pointed out by the literature. Security and privacy are of great importance, and the system should be secure enough to stop any probable misuse and be capable enough to follow privacy policies. Even though the case company seems to have a stable IT infrastructure, transition toward such a system seems very challenging because it requires great organizational effort, expanding competences, and significant investment on data infrastructures.

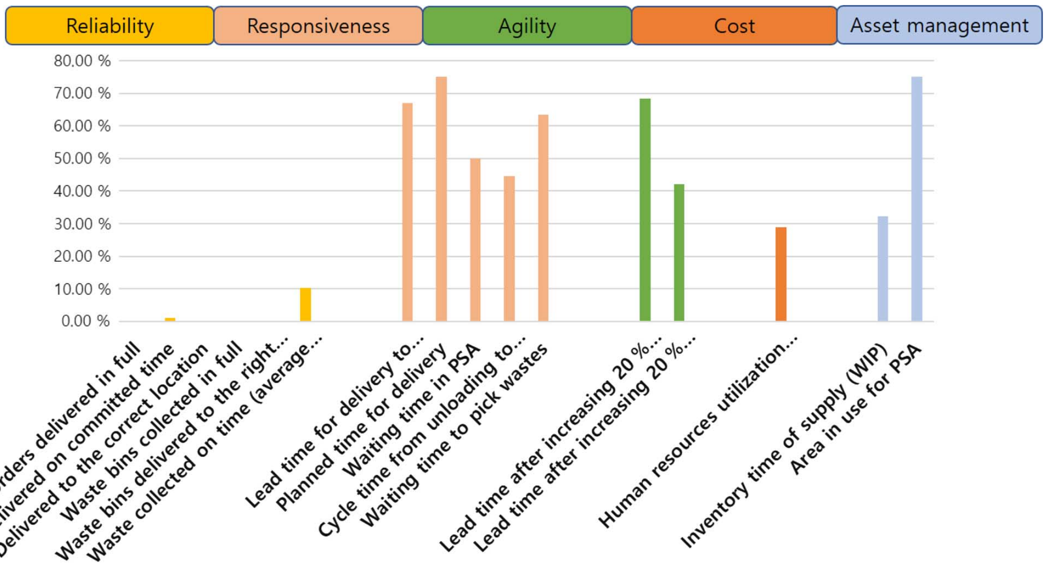
CONSEQUENCES OF INTRODUCING TECHNOLOGIES ENABLING DATA-DRIVEN PRODUCTION LOGISTICS

As can be seen in figure 8, implementing data-driven technologies has nonhomogeneous effects on production logistics (from a SCOR perspective). The case company already has a high level of reliability, and implementation of these technologies does not have a considerable effect on reliability. In the case of responsiveness, the effects are noticeable. Lead times, waiting times, and queue length are reduced. The system becomes more agile after implementing data-driven technologies in terms of improved delivery time. The cost is also positively affected, but it is difficult to be sure on this because the overall cost of implementing data-driven technologies is unclear and needs a detailed investigation. In general, asset management has also experienced a better situation considering 'area in use' and 'inventory time of supply'.

In conclusion, this research explored the benefits and challenges of data-driven production logistics. Because the number of empirical studies in this area is limited, this research performed a single case study at a site within an international pharmaceutical company. This will help researchers to find a more realistic picture regarding transition toward digitalization and specially implementing data-driven technologies. The results of this research can be useful for industries to find out how the topics discussed here can improve their understanding regarding the applications, benefits, and challenges. Additionally, this research helps companies to have realistic expectations for the implementation of data-driven production logistics.

The literature was reviewed in order to find out the potential benefits and challenges of a transition toward data-driven production logistics. To meet the objective of this article, three research questions concerning the potential benefits, challenges, and consequences of implementing data-driven technologies have been discussed. The literature review, interview, and simulation were deployed as data collection methods. The findings of this research are in line with the potential benefits mentioned in the literature, although examining all the claimed potential benefits is not possible in one single case study and requires further analysis.

FIG. 8 Effect of simulated implementation of data-driven technologies on SCOR attributes.



The simulation results indicate that deploying a data-driven framework will facilitate utilization of data in a proactive manner. Overall performance of the system will be improved in terms of responsiveness, agility, and asset management. Even though cost was concluded to be positively affected, more detailed investigations need to be done regarding the overall cost of transition. However, the findings show that the production logistics of the case company are reliable and implementing data-driven technologies will not have a significant effect on it. Analysis of the current situation shows that the logistics processes need to be improved through conventional waste reduction methods. This should be made before any effort for transition toward data-driven production logistics.

As most of the concepts related to smart manufacturing and data-driven production logistics are rather unclear, the case company is more focused on increasing the level of automation rather than deploying data-driven frameworks and technologies. This has been reflected in their vision to reduce the number of human touches by increasing the level of automation. Even though the number of touches will be reduced in data-driven production logistics, this improvement is not significant. This implies that reducing the number of touches and increasing the level of automation do not necessarily increase value.

Even though the existing frameworks are necessary for clarifying data-driven production logistics, the case company requires a clear understanding regarding the applications, potentials, and challenges as well as a road-map for transition. It seems that investigating the possibility of providing a more detailed roadmap for transition toward data-driven production logistics is necessary and is proposed for further study.

ACKNOWLEDGMENTS

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Appendix

TABLE A1
Simulation time and number of available resources

Simulation Time	25,200 min (20 Working Days in One Month, 21 Working Hours Per Day)
Resource transit hall	3 persons
Resource line A	2 persons
Resource line B	2 persons

TABLE A2
As-is situation

Parameters in ExtendSim	Run 1	Run 2	Run 3	Run 4	Average
Created items (number of pallets)	3,165	3,165	3,165	3,165	3,165
Exited items (number of pallets)	3,097.00	3,070.00	3,068.00	3,090.00	3,081.25
Delivery time A	106.00	146.00	185.00	106.00	135.75
Delivery time B	97.00	124.00	127.00	116.00	116.00
Delivery time C	65.00	66.00	79.00	65.00	68.75
Number of handled waste bins	2,195.00	2,245.00	2,210.00	2,241.00	2,222.75
Cycle time before dispatch to lines	30.00	33.00	44.00	31.00	34.50
Average waiting time for bins, line A	9.13	11.30	9.33	7.70	9.37
Average waiting time for bins, line B	7.20	7.20	5.90	7.80	7.03
Average waiting time for bins, line C	1.36	1.80	3.20	1.01	1.84
Resource utilization transit hall	63 %	64 %	68 %	63 %	0.65
Resource utilization line A	89 %	87 %	85 %	87 %	0.87
Resource utilization line B	86 %	89 %	92 %	88 %	0.89

TABLE A3
To-be situation

Parameters in ExtendSim	Run 1	Run 2	Run 3	Run 4	Average
Created items (number of pallets)	3,165	3,165	3,165	3,165	3,165
Exited items (number of pallets)	3,100.00	3,095.00	3,084.00	3,105.00	3,096.00
Delivery time A	36.00	35.00	36.00	37.00	36.00
Delivery time B	36.00	35.00	36.00	35.00	35.50
Delivery time C	33.00	34.00	34.00	34.00	33.75
Number of handled waste bins	2,233.00	2,235.00	2,230.00	2,222.00	2,230.00
Cycle time before dispatch to lines	19.00	19.00	19.00	19.50	19.13
Average waiting time for bins, line A	3.90	3.20	2.90	2.90	3.23
Average waiting time for bins, line B	3.80	2.90	3.20	2.70	3.15
Average waiting time for bins, line C	0.30	0.50	0.50	0.36	0.42
Resource utilization transit hall	42 %	42 %	42 %	42 %	0.42
Resource utilization line A	56 %	55 %	56 %	55 %	0.56
Resource utilization line B	55 %	55 %	56 %	55 %	0.55

Note: All the times are in minutes.

TABLE A4
As-is agility by 20 % increase in raw material

Agility Parameter	Run 1	Run 2	Run 3	Average
Lead time after 20 % increase in raw material, line A	1,249	1,461	1,057	1,405
Lead time after 20 % increase in raw material, line B	1,161	1,416	1,044	1,207
Lead time after 20 % increase in raw material, line C	1,094	1,326	938	1,119.3333
Delivery	3,302	3,348	3,403	3,351

TABLE A5
To-be agility by 20 % increase in raw material

Agility Parameter	Run 1	Run 2	Run 3	Average
Lead time after 20 % increase in raw material, line A	433	287	574	431.33333
Lead time after 20 % increase in raw material, line B	438	261	573	424
Lead time after 20 % increase in raw material, line C	333	167	471	323.66667
Delivery	3,566	3,597	3,492	3,551.6667

TABLE A6
As-is agility by 20 % increase in delivery

Agility Parameter	Run 1	Run 2	Run 3	Average
Lead time after 20 % increase in delivery, line A	163	224	190	192.33333
Lead time after 20 % increase in delivery, line B	107	145	151	134.33333
Lead time after 20 % increase in delivery, line C	65	103	96	88
Delivery	3,702	3,711	3,699	3,704

TABLE A7
To-be agility by 20 % increase in delivery

Agility Parameter	Run 1	Run 2	Run 3	Average
Lead time after 20 % increase in delivery, line A	93	87	83	87.666667
Lead time after 20 % increase in delivery, line B	113	87	98	99.333333
Lead time after 20 % increase in delivery, line C	60	54	53	55.666667
Delivery	3,702	3,703	3,714	3,706.3333

TABLE A8
ExtendSim activities' parameters in simulation of the as-is situation

			Processing Time, min				Shutdown, min	
Activity Name	Distribution	Number of Resource	Minimum	Maximum	Most Likely	Maximum Item in Activity	Time Between Failure	Time To Repair
Unloading truck	Triangular	1	1.5	2.5	2	1	…	…
Barcode scanning	Triangular	1	0.3	5	0.5	1	…	…
Storage and ERP update	Triangular	1	2	3	2.5	1	…	…
Pick the pallet from storage	Triangular	1	1	2	1.5	1	…	…
Load to conveyor A	Triangular	1	0.5	5	0.75	1	…	…
Load to conveyor B	Triangular	1	0.5	5	0.75	1	…	…
Load to conveyor C	Triangular	1	0.5	5	0.75	1	…	…
Unload and pallet exchange A	Triangular	1	1	40	2	1	Triangular Min 450 Max 510 Most likely: 480	42
Unload and pallet exchange B	Triangular	1	1	40	1.5	1	Triangular Min 450 Max 510 Most likely: 480	42
Unload and pallet exchange C	Triangular	1	1	40	1.5	1	Triangular Min 450 Max 510 Most likely: 480	42
Approach the elevator and wait	Triangular	1	0.5	5	1	1	…	…
Approach PSA B	Triangular	1	0.5	5	1	1	…	…
Approach PSA C	Triangular	1	0.5	5	1	1	…	…
Delivery to PSA line A	Triangular	1	1	5	1.5	1	…	…
Delivery to PSA line B	Triangular	1	1	5	1.5	1	…	…
Delivery to PSA line C	Triangular	1	1	5	1.5	1	…	…
Waste handling line A	Triangular	1	7	45	20	1	30	1
Waste handling line B	Triangular	1	7	45	20	1	30	1
Waste handling line C	Triangular	1	7	45	20	1	30	1

TABLE A9
ExtendSim activities' parameters in simulation of the as-is situation

			Processing Time, min				Shutdown, min	
Activity Name	Distribution	Number of Resource	Min	Max	Most Likely	Maximum Item in Activity	Time between Failure	Time to Repair
Unloading truck	Triangular	1	1.5	2.5	2	1	…	…
Storage and ERP update	Triangular	1	2	3	2.5	1	…	…
Pick the pallet from storage	Triangular	1	1	2	1.5	1	…	…

TABLE A9 *Continued*

Activity Name	Distribution	Number of Resource	Processing Time, min Min	Max	Most Likely	Maximum Item in Activity	Shutdown, min Time between Failure	Time to Repair
Load to conveyor A	Triangular	1	0.5	5	0.75	1	…	…
Load to conveyor B	Triangular	1	0.5	5	0.75	1	…	…
Load to conveyor C	Triangular	1	0.5	5	0.75	1	…	…
Unload and pallet exchange A	Triangular	1	1	40	2	1	Triangular Min 450 Max 510 Most likely: 480	42
Unload and pallet exchange B	Triangular	1	1	40	1.5	1	Triangular Min 450 Max 510 Most likely: 480	42
Unload and pallet exchange C	Triangular	1	1	40	1.5	1	Triangular Min 450 Max 510 Most likely: 480	42
Approach the elevator and wait	Triangular	1	0.5	2*	1	1	…	…
approach PSA B	Triangular	1	0.5	5	1	1	…	…
approach PSA C	Triangular	1	0.5	5	1	1	…	…
Delivery to PSA line A	Triangular	1	1	5	1.5	1	…	…
Delivery to PSA line B	Triangular	1	1	5	1.5	1	…	…
Delivery to PSA line C	Triangular	1	1	5	1.5	1	…	…
Waste handling line A	Triangular	1	7	45	20	1	30	1
Waste handling line B	Triangular	1	7	45	20	1	30	1
Waste handling line C	Triangular	1	7	45	20	1	30	1

Note: * Waiting for elevator is eliminated in to-be scenario.

TABLE A10
Other items' specifications in the ExtendSim model

Item	Specifications (As-Is)	Specifications (To-Be)
Scanning queue	Infinity length	Will be removed
Select item out after scanning	Storage: 0.1 Line A: 0.35 Line B: 0.35 Line C: 0.2	Storage: 0.1 Line A: 0.35 Line B: 0.35 Line C: 0.2
Picking from storage queue	Max queue length: 70	Max queue length: 70
Unloading conveyor A queue	Max queue length: 12	Max queue length: 12
Unloading conveyor B queue	Max queue length: 10	Max queue length: 10
Unloading conveyor C queue	Max queue length: 4	Max queue length: 4
Conveyor A	Capacity: 1 Travel time: 1 min	Capacity: 1 Travel time: 1 min
Conveyor B	Capacity: 1 Travel time: 1 min	Capacity: 1 Travel time: 1 min
Conveyor C	Capacity: 1 Travel time: 1 min	Capacity: 1 Travel time: 1 min
Elevator	Capacity: 1 Travel time: 0.75 min	Capacity: 1 Travel time: 0.75 min

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