Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

DIGITAL TWIN-BASED SERVICES FOR SMART PRODUCTION LOGISTICS

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ABSTRACT

Digital Twin (DT)-based services including Industrial Internet of Things (IIoT) are essential for achieving the vision of Smart Production Logistics and enhancing manufacturing competitiveness. DT-based services combining IIoT provide real-time location of materials and optimization of resources for addressing mass customization and fluctuating market demand. However, literature applying IIoT and achieving DT-based services in Smart Production Logistics (SPL) is scarce. Accordingly, the purpose of this study is to analyze the combined use of DT-based services and IIoT in SPL. We propose a framework combining DT-based services and IIoT for the real-time location and optimization of material handling. The study draws results from an SPL demonstrator based on a case in the automotive industry applying the proposed framework. The results show improvement in the delivery, makespan, and distance travelled during material handling. The study provides critical insight for managers responsible for improving the delivery of materials and information inside a factory.

1 INTRODUCTION

Digital Twins (DTs) and Industrial Internet of Things (IIoT) are increasingly perceived as critical enablers for improving the movement of materials and information inside factories (Lu et al. 2020; Park et al. 2020), and essential for enhancing manufacturing competitiveness (Ben-Daya et al. 2019). Manufacturing companies combining DTs and IIoT may achieve real-time location of materials and improve reaction to sudden changes, which are essential for addressing mass customization and fluctuating market demand in future PL settings (Ivanov et al. 2019). On the one hand, IIoT provides a digital network of physical objects facilitating real-time information for sensing, monitoring and managing the flow of materials and information (Qu et al. 2016). On the other hand, DTs offer a counterpart to the real-time information originating from IIoT. DTs simulate, predict, and optimize behaviors in a bi-directional relation between a manufacturing system and its virtual representation (Zhou et al. 2020). Moreover, DTs and IIoT are

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

essential components for achieving the vision of Smart Production Logistics (SPL). SPL includes applying digital technologies for planning, implementing, and controlling the efficient flow of materials or information, and achieving active perception, response, and autonomous decision-making in real-time (Ding et al. 2020; Liu et al. 2020).

Research contends that efforts targeting IIoT and DTs separately may be insufficient for realizing the vision of SPL. Instead, manufacturing companies must develop DT-based services providing holistic comprehension including both real-time location and optimization (Qi and Tao 2019). DT-based services refer to the component of DTs using multiple data, resources, and distributed computing, and offering advanced, intuitive, and ubiquitous understanding for people or devices (Longo et al. 2019). The literature presents a limited number of studies applying IIoT and achieving DT-based services in SPL (Cimino et al. 2019). Developing a framework applying IIoT and DT-based services in SPL is necessary for targeting the high operational dynamics, intensive human involvement, and uncertain events on the factory floor common in the execution of SPL (Guo et al. 2021). Failing to combine IIoT and DT-based services, manufacturing companies remain exposed to ill-conceived solutions, and stand at the threshold of achieving the full potential of real-time location and optimization in SPL.

Addressing this problem, the purpose of this study is to analyze the combined use of DT-based services and IIoT in SPL. The study proposes a framework specifying DT-based services including IIoT for achieving the real-time location and optimization of material handling. We draw results from an SPL demonstrator based on a case at an automotive manufacturer. The results suggest that DT-based services including IIoT enhance the execution of material handling and lead to improvements of delivery, makespan, and distance. This study provides critical insight for managers responsible for improving the delivery of materials and information inside a factory. The remainder of this study is organized as follows. Section 2 describes related works. Section 3 proposes a DT-based framework for SPL. Section 4 presents the results of a case applying IIoT and achieving DT-based services. Section 5 discusses the implications of this study. Section 6 concludes and suggests future research.

2 RELATED WORKS

This section reviews extant research about DT-based services and IIoT in SPL. First, the section describes existing understanding of DT-based services, conceptual frameworks, and enabling technologies, and simulation tools. Then, the section establishes the importance of IIoT for developing real-time location applications. The goal of a DT-based service is to provide users with value-adding services, such as monitoring, simulation, verification, virtual experiment, optimization, digital education, etc. (Qi et al. 2018). DT-based services provide a link between the needs of stakeholders at different levels of a manufacturing company, and the virtual and real-world solutions originating from a DT (Ding et al. 2019). For example, staff with no professional abilities for processing massive data may access DT-based services to answer problems related to diagnosis, prognosis, location, or reducing cost and downtime (Qi, et al., 2018).

Research highlights the importance of developing all aspects of a DT for realizing DT-based services. DTs involve virtual models simulating and providing feedback to the behavior of physical objects in the real world (Tao, Zhang, et al. 2019). DTs present results from simulation models including the use of real-time data and resulting in value-added services essential for the providing staff feedback (Gyulai et al. 2020; Latif et al. 2020). Longo et al. (2019) propose a five-component architecture for achieving DT-based services. A first component involves actuators, sensors, and IIoT devices seamlessly exchanging data. A second component includes a DT in real-time synchronization with the physical factory. A third component comprehends ERP systems providing the understanding of the manufacturing process, schedule, and structure. A fourth component comprises an enterprise bus facilitating data exchange. Finally, the fifth component involves web or mobile applications connecting key stakeholders to DT-based services. Because of its importance, the concept of a DT-based service is proposed as one of the five key dimensions of a DT including a physical factory, a virtual factory, data connection and storage, and DT-based services. Figure 1 presents the five dimensions of a DT including DT-based services according to Tao, Qi, et al. (2019).

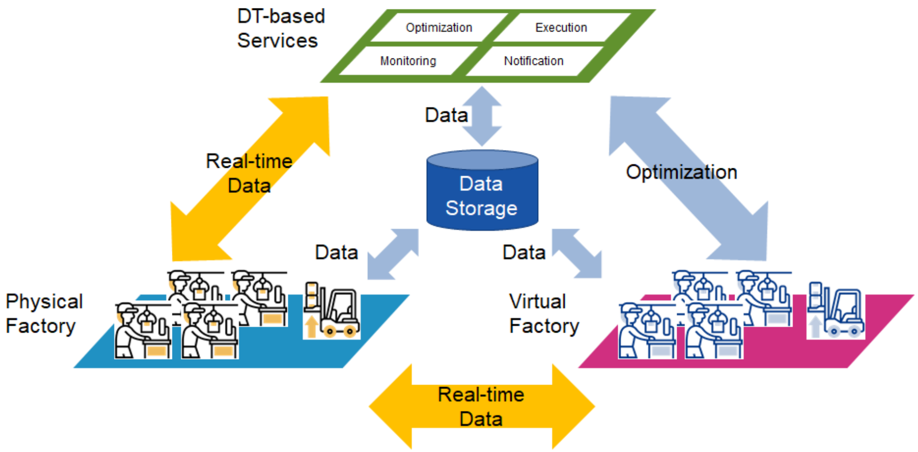

Figure 1: Five dimensions of DTs including DT-based services according to Tao, Qi, et al. (2019).

Recent research efforts suggest the importance of DT-based services for SPL. For example, Jeong et al. (2020) propose a process for the design of DTs in SPL. Zhang (2018) analyzes the benefits of DTs for job shop scheduling. Wang et al. (2020) propose a proactive material handling method including a CPS, and a DT model for monitoring the status of real-life objects and analyzing production performance indicators. Park et al. (2020) present an architectural framework of DT-based services for supply chain control. Accordingly, current research efforts underscore the importance of DT-based services for monitoring, predicting, optimizing and controlling PL and targeting the needs of operators, engineers, and managers (Longo et al. 2019).

IIoT is an essential Industry 4.0 technology. IIoT refers to a system of networked objects, cyber-physical assets, associated generic information technologies, and optional cloud or edge computing platforms (Boyes et al. 2018). The purpose of IIoT is that of connecting all industrial assets, including machines and control systems, with the information systems and the business processes for increasing production value (Sisinni et al. 2018). Increasingly, research applying IIoT in SPL targets real-time location of materials and resources. Real-time location concerns locating, tracking, and monitoring manufacturing resources for optimizing the management of resources (Guo et al. 2021). Achieving real-time location in SPL is inherently tied to IIoT facilitating the use of smart objects and communication in the manufacturing system (Qu et al. 2016). Research has invested significant efforts in applying IIoT and achieve real-time location in SPL (Zhang et al. 2015)

3 PROPOSING A FRAMEWORK FOR DIGITAL TWIN-BASED SERVICE IN SMART PRODUCTION LOGISTICS

In this section, we propose a framework for DT-based services for material handling in SPL. The framework applies five dimensions of DTs including a physical environment, data connection, virtual environment, data storage, and DT-based services according to Tao, Qi, et al. (2019). The framework describes DT-based services targeting distinct stakeholders including operators, logistics and factory managers.

The physical environment includes resources executing, and IIoT devices sending and receiving data about material handling tasks. Resources comprehend forklifts and or additional material handling equipment. IIoT devices include Ultra Wide Band (UWB) tags attached to forklifts send data to the sensce points which is connected to network.

Data connections facilitate the transfer of data and information between physical and virtual environments. Data and information between the different environments can be transferred using Application Programing Interfaces (APIs). Accordingly, information from the virtual environment may be extracted for its use for example in simulation models or material handling equipment so long as a API exists. Additionally, the framework has a middleware for publishing, collecting, and storing data from devices, and storing and fetching information from databases. Open source projects Apache Kafka and Node-RED were used as a data streaming bus and application layer considering the versatility and scalability.

Data storage realizes the accumulation of information necessary to providing DT-based services for material handling. This study applies a Linux virtual machine as a server and databased in four aspects critical for the delivery of materials. First, the storage of data from an order delivery schedule specifying the id, order number, part, description, and consumption and pickup time and location. Second, information regarding the movement of forklifts including the name, time, location, distance, velocity, and acceleration of forklifts. Third, results from optimization schedule of material handling tasks specifying the forklift, order number, and consumption and pickup time and location. Fourth, virtual representation of layout, resources, and process for material handling.

The virtual environment provides a digital representation of material handling involving a task scheduling optimizer, a material handling model, and a web-based route and a real-time location applications. The task scheduling optimizer applies a dynamic optimization method for obtaining the schedule of material handling tasks minimizing the delivery, makespan, and energy (e.g. distance). The web-based route application displays the results of the task scheduling optimizer showing in a virtual layout the pickup and delivery locations, and a predetermined route connecting both locations. Additionally, the virtual layer includes a 3-D model of material handling developed in the gaming engine Unity. This model includes the manufacturing process, forklifts, products, and provides a real-time virtual representation of material handling. Finally, the virtual environment includes a real-time location application displaying data from the RTLS tags including sphagetting diagrams, heat maps, and utilization, collisions, and distance travelled by the forklifts. In addition, the virtual environment can include an optimization algorithm or a simulation model for material handling testing scenarios prior to their implementation in a physical environment. This model can derive optimized results by using various parameters and control variables that can describe the production logistics environment. Moreover, this model presents results including the stochastic analysis of different scenarios.

Importantly, DT-based services in SPL must address the concerns of stakeholders with distinct responsibilities and information needs. A service can be defined as the application of specialized competencies (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself (Hohmann and Posselt 2019). The proposed framework for DT-based services in SPL exemplifies the information needs of stakeholders by focusing on the responsibilities of material handling operators, logistics managers, and factory managers. Figure 2 presents DT-based service framework for SPL.

The first group of stakeholders include the material handling operators. DT-based services may benefit operators by providing the location of all forklifts, or the distance to points of pickup and delivery. Additionally, DT-based services facilitate and enhance the safety of material handling operators by providing information about speed, vibration, or impact of forklifts. DT-based services targeting material handling operations can be utilized even when the material handling system is fully automated in SPL. For example, DT-based services may target the management of AGV fleets, or interact with automated warehousing, packaging, kitting or manufacturing systems.

The second group of stakeholders involve logistics managers. Logistics managers need services for operating production plans and a holistic understanding about the movement of material and information. Therefore, DT-based services focus on optimizing schedules including the pickup and delivery of material. Optimization models defined in a virtual environment can provide an optimal schedule linked to a production plan. Additionally, logistics managers may benefit from DT-based services by monitoring the execution of material handling tasks, and extend their analysis for including historical and real-time data. Accordingly, logistics managers may prescribe actions for originating from DT-based services.

Factory managers constitute a third group of stakeholders benefiting from DT-based services. Factory managers need a predictive service that considers the interrelation of SPL with other subsystems of a manufacturing system. Correspondingly, DT-based services may offer factory managers information concerning the delivery, makespan, and energy (e.g. distance) of material handling and their implications to the manufacturing system.

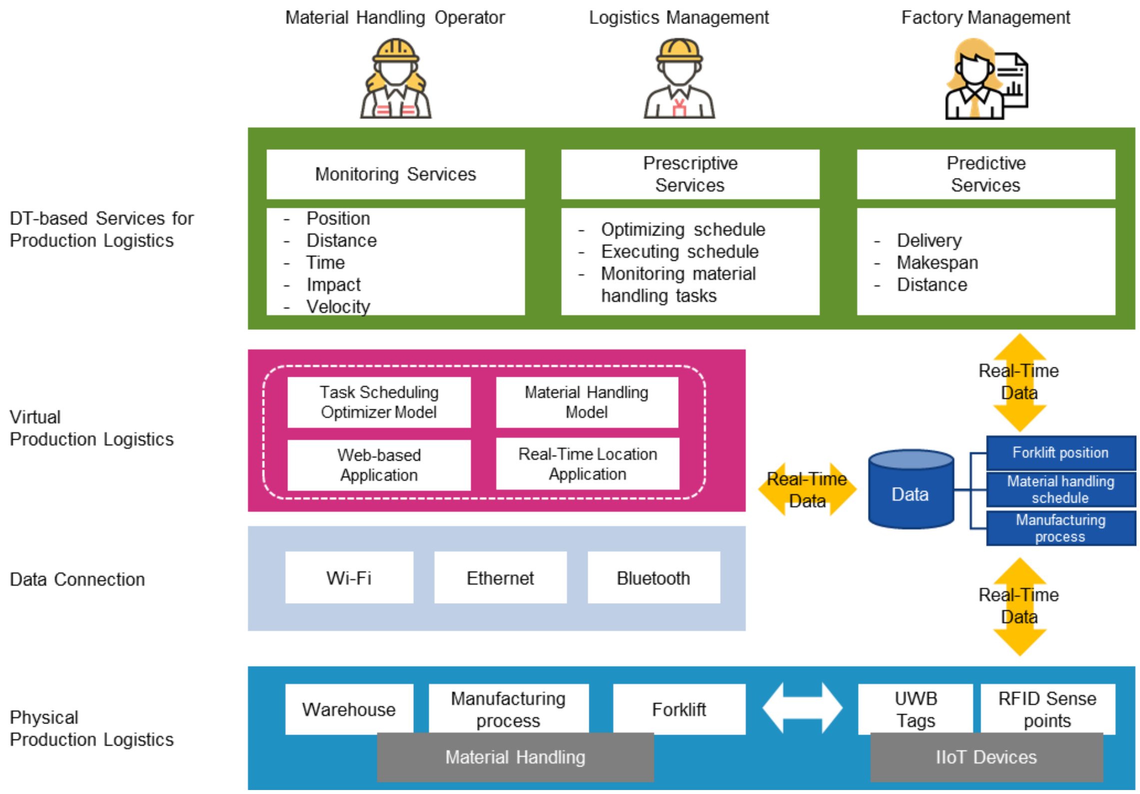

Figure 2: A framework for DT-based services in SPL.

4 CASE STUDY

The section presents a case from an automotive company in Sweden. The company assembles full vehicles and manufactures its own transmission components. Manually operated forklifts perform material handling tasks including delivery of supplies from warehouse to production of transmissions, and transfer of parts from earlier to later stages of production of transmissions. The forklift executes a schedule including 25 material handling tasks. Current material handling practices relying on staff intuition are insufficient for meeting an increasing variety of scheduled products and supplies. Forklift operators struggle locating the point of pickup and delivery of parts and determining the sequence of scheduled tasks. Logistics managers struggle with understanding the reasons for deviations of scheduled tasks, and improving delivery, makespan, and distance of material handling. Therefore, the company requires urgent solutions involving real-time location and task scheduling optimization in material handling.

An SPL demonstrator is developed in our laboratory including DT-based services and IIoT for material handling based on the proposed framework. The SPL demonstrator includes a physical environment including material handling resources and IIoT devices, data connection, data storage, virtual environment, and DT-based services for SPL. The physical component of the SPL demonstrator represents the material handling for the production of transmissions including a warehouse, up to three forklifts (represented by individuals transferring parts among delivery points), and three production processes (e.g. soft machining, heat treatment, and hard machining). Soft machining contains two points of material delivery (A and B). Heat treatment includes one point of material delivery (C). Hard machining contains two points of material delivery (D and E), and one point of delivery for shipping the finalized products (F). The warehouse comprises three points for material pickup (W1, W2, and W3).

The SPL demonstrator includes an automatic generator of material handling task representing an ERP system. The generator creates a schedule including the delivery of supplies from the warehouse to the production of transmissions, and transfer of parts from earlier to later stages of production of transmissions. The schedule generator specifies an order number, the type of task (e.g. delivery of supplies or transfer of parts), the time for delivery and consumption, and the point of pickup and delivery of material handling tasks. The material handling task schedule generator utilizes statistical functions for randomizing and adding variability to material handling tasks. The statistical functions can be adjusted to replicate the variability in the production of transmissions. Table 1 presents the schedule for material handling tasks. The schedule specifies the order number, type of task (e.g. delivery of supplies or transfer of parts), time for pickup and delivery of material, and pickup and delivery locations.

Table 1: Schedule for material handling tasks in the SPL demonstrator

Order Number	Task Type	Pickup Time (minutes)	Duration (minutes)	Delivery Time (minutes)	Pickup Location	Delivery Location
1	Delivery	17:00	00:55	17:55	W1	A
2	Delivery	22:12	01:22	23:34	W1	B
3	Delivery	09:57	00:27	10:24	W2	C
4	Delivery	07:52	04:32	12:24	W3	D
5	Delivery	14:48	04:40	19:28	W3	E
6	Transfer	19:15	00:30	19:45	A	C
7	Transfer	13:31	00:30	14:01	A	C
8	Transfer	14:21	00:30	14:51	A	C
9	Transfer	03:43	00:39	04:22	B	C
10	Transfer	10:21	00:39	11:00	B	C
11	Transfer	22:10	00:39	22:49	B	C
12	Transfer	09:20	04:40	14:00	C	D
13	Transfer	11:15	04:40	15:55	C	D
14	Transfer	04:54	04:40	09:34	C	D
15	Transfer	08:46	04:48	13:34	C	E
16	Transfer	09:04	04:48	13:52	C	E
17	Transfer	14:46	04:48	19:34	C	E
18	Transfer	22:17	00:46	23:03	D	F
19	Transfer	15:38	00:46	16:24	D	F
20	Transfer	23:37	00:46	24:23	D	F
21	Transfer	13:53	00:46	14:39	D	F
22	Transfer	23:38	01:02	24:40	E	F
23	Transfer	02:05	01:02	03:07	E	F

24	Transfer	03:54	01:02	04:56	E	F
25	Transfer	16:03	01:02	17:05	E	F

Data connection in the SPL demonstrator begins with IIoT devices. The SPL demonstrator includes one UWB tag for each individual representing a forklift, and 25 sense points collecting real-time information of the forklift. The accuracy of the UWB tags is of 10 cm. Real-time information includes speed, distance, GPS coordinates, vibration, and time. Additionally, digitally generated delivery zones register the arrival and departure of the forklift to every point of delivery. Figure 3 presents the layout and material handling for the production of transmissions represented in the SPL demonstrator.

Real-time information of the UWB tag is transferred from the sense points to the cloud server. Then, real-time information is acquired from the cloud server using predefined protocol and API. In this case Signal R protocol was used. It transmits information whenever the forklift departs or arrives at a delivery point, moves or standstill.

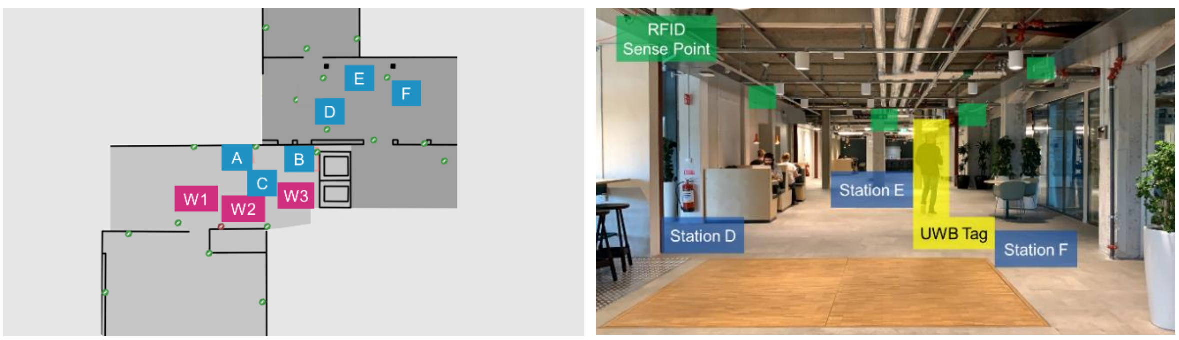

Figure 3: Layout and material handling for the production of transmissions represented in the SPL demonstrator.

The virtual environment of the SPL demonstrator involves a web-based application, a real-time location application, a task scheduling optimization and a material handling simulation model. The web-based application displays real-time movement, traces prior positions, generates a heat map of a forklift, and identifies forklifts individually. The real-time location application utilizes real-time location information as an input. The real-time location application draws the forklift position in 2-D, and shows the concentration of forklift activity. The task scheduling optimization model receives a list of tasks from the task schedule generator, and optimizes the tasks according to delivery, makespan, and distance. The material handling simulation model considers historical data as an input and produces a stochastic prognosis of delivery, makespan, distance, and forklift utilization. DT-based services in the SPL demonstrator target three levels of seniority including material handling operators, logistics managers, and factory management. DT-based services for material handling operators include information of position, distance, and time for material handling tasks. DT-based services for logistics managers comprise optimizing and executing material handling schedule, and monitoring the execution of material handling tasks. DT-based services for factory management include assessing delivery, makespan, and distance in material handling.

5 RESULTS

This section presents results from the SPL demonstrator validating the DT-based service framework for SPL. The results include the execution of the same schedule in two scenarios. In the first scenario, forklift operators execute the schedule ad hoc. Forklift operators arrange and deliver chronologically material handling tasks according to the earliest delivery time. In the second scenario, forklift operators utilize DT-based services utilizing IIoT. The DT-based services apply a real-time data-driven dynamic optimization method for obtaining an optimal schedule of material handling tasks. The study evaluates both scenarios including four Key Performance Indicators (KPIs) (e.g. distance, delivery, makespan, and distance of material handling tasks).

The first result involves the ad hoc execution of material handling tasks. The ad hoc execution includes one forklift delivering all material handling tasks in Table 1. Figure 4 shows that Orders two and ten in the schedule were delivered late and are marked red in Figure 4. Real-time location data collected from IIoT devices in the SPL demonstrator present the results for distance travelled by the forklift, delivery, and makespan. Table 2 shows the results of ad hoc execution of material handling tasks. Respectively, the results for the KPIs of ad hoc execution include 852,01 meters travelled, two late deliveries, and a makespan of 23, 48 minutes.

Table 2: Results of ad hoc execution of material handling tasks

Forklift	Task Execution Order	Distance (meters)	Late Deliveries	Makespan (minutes)
1	22, 20, 18, 2, 11, 6, 1, 25, 19, 5, 17, 8, 21, 7, 13, 10, 3, 12, 16, 15, 4, 14, 24, 9, 23	852,01	2 (Orders 2 and 10)	23:48

A second result involves DT-based services apply a real-time data-driven dynamic optimization method for obtaining an optimal schedule of material handling tasks. The detailed optimization procedure follows. Forklifts and tasks are divided into n sub-regions on the basis of their current locations. Matrices F and T correspondingly capture real-time information of forklifts and tasks. Then, n tasks and m forklifts subsets are formed as $T = (T_1, T_2, T_3, \cdots, T_n)^T$, and $F = (F_1, F_2, F_3, \cdots, F_m)^T$. In this case, tasks and forklifts in the same region are divided into identical subsets, and form the pre-optimized sets (T_i, F_i), $i \in [1,n]$, and $j \in [1,m]$. For (T_i, F_i), the current location and destination could be constructed as task vector $T_i(CP_i, ND_i)$ and vehicle vector $V_i(CP_i, ND_i)$. Table 3 describes the notation for the real-time information-driven dynamic optimization.

$$T = \left| T_3 \quad PT_3 \quad CT_3 \quad CP_3 \quad ND_3 \quad d_3 \quad \mu_3 \right|$$

$$F = \left| F_3 \quad SW_3 \quad SV_3 \quad CP_3 \quad ND_3 \quad C_3 \quad L_3 \right|$$

A dynamic pre-optimization model for tasks is proposed shown including the following steps.

Step 1: construct the optimization function.

$$f(V_i) = minarccos[(T_i F_i)/(|T_i||F_i|)] \tag{1}$$

$$W_i \leq SW_i, V_i \leq SV_i, i \in [1, n], j \in [1, m] \tag{2}$$

Step 2: forklift vector $F_i(CP_i, ND_i)$ and task vector $T_i(CP_i, ND_i)$ are substituted into (1). If ND_i=free, then free T_i.

Step 3: tasks mapped with the obtained minimal value of the above-mentioned function is allocated to forklift j. The pre-allocated set for each task is built as follows.

$$T_i = (F_1, F_2, F, \cdots, V_x), i \in [1,n], x \in [1,m] \tag{3}$$

Table 3: Notation for the real-time information-driven dynamic optimization

Notation	Description
$F = \{F_1, F_2, F_3, \dots, F_n\}$	Forklift set (can be forklift or AGV)
$T = \{T_1, T_2, T_3, \dots, T_m\}$	Task set
F_j	Forklift j

$\vec{V_i}$	Vehicle vector of $V_i = (CP_i, ND_i)$
$SV_i = (l_f, w_f, h_f)$	Surplus volume of V_i: length, width, and height
SW_i	Surplus weight of F_i
$CP_i = (x_{fi}, y_{fi})$	Current position of F_i: X-axis and Y-axis position
$ND_i = (x'_{fi}, y'_{fi})$	Next destination of F_i: X-axis and Y-axis position
C_i	Oil consumption per hour of F_i
L_i	Oil consumption of F_i
T_i	Task i (Task plan)
$\vec{T_i}$	Task vector of T_i
PT_i	Pickup time of task T_i
CT_i	Delivery time of task T_i
$\widetilde{PT}_i$	Actual pickup time of task T_i
$\widetilde{DT}_i$	Actual delivery time of task T_i
$CP_i = (x_{ti}, y_{ti})$	Current position of T_i: X-axis and Y-axis position
$ND_i = (x'_{ti}, y'_{ti})$	Next destination of T_i: X-axis and Y-axis position
d_i	Duration time of task
μ_i	Task type of task T_i
dt_i	Time of delivery delay of T_i
DT	Total time of delivery delay of tasks
M	Makespan of finishing all the tasks
TF	Time consumption of forklift
D_i	Distance of forklift F_i
V_i	Velocity of forklift F_i

Step 4: pre-allocated sets are classified into three classes, namely Class 1: x=0, Class 2: x=1, and Class 3: $x \geq 2$.

Step 5: a multi-objective optimization function for tasks in Class 3 is formulized as follows. Accordingly, the motivation for the multi-objective optimization function is that of minimizing the delivery times, make span, and travelled distance by the forklift where precedence is given to the ontime delivery of materials.

$$f = \min(w_1 * DT + w_2 * M + w_3 * TF) \tag{4}$$

Step 6: the forklift with the minimal value of (4) in a global optimization is responsible for distributing T_i. Other forklifts are free.

Step 7: tasks in Class 1 return to Step 1. The task in Class 2 is loaded and distributed to the optimized forklifts.

Step 8: End.

(5) represents the time of the delivery delay of tasks. (6) and (7) are the makespan of finishing all the tasks and time consumption of the forklifts finishing all the tasks.

$$DT = \sum_i^n dt_i\,, \quad \widetilde{PT}_i \geq PT_i \tag{5}$$

$$M = \max(\widetilde{DT}_i - \widetilde{PT}_i) \tag{6}$$

$$FT = \sum_{i=1}^{m} D_i/V_i \tag{7}$$

The simulation of data-driven dynamic optimization within DT-based services minimizes the objectives of distance, makespan, and delivery. Up to three forklifts and the 25 material handling tasks are chosen as simulated objects. The results of the DT-based services applying a real-time data-driven dynamic optimization method for material handling tasks are presented in Table 4. These results show the need for three forklifts. Task execution order for forklift 1 includes Orders number 23, 24, 3, 10, 7, 8, 17, 5, 25, 18, and 22; forklift 2 includes Order number 9, 14, 4, 15, 16, 12, 13, 21, 19, and 20; forklift 3 includes Order number 1, 6, 11, and 2 respectively. The distances travelled by forklifts 1, 2, and 3 are 236.59, 397.80, and 31.43 meters, respectively. The total distance travelled by forklifts 1, 2, and 3 is 665,83 meters. Forklifts 1, 2, and 3 do not incur late deliveries. Finally, the makespan that of is 23:42 minutes.

Table 4: DT-based services applying a real-time data-driven dynamic optimization method for material handling tasks

Forklift	Task execution order	Distance (meters)	Late deliveries	Makespan (minutes)
1	23, 24, 3, 10, 7, 8, 17, 5, 25, 18, 22	236,59	0	23:42
2	9, 14, 4, 15, 16, 12, 21, 19, 10	397,80	0	23:40
3	1, 6, 11, 2	31,44	0	22:19
	Total	665,83		

6 DISCUSSION AND IMPLICATIONS

The purpose of this study was to analyze the combined use of DT-based services and IIoT in SPL. In particular, this study focused on real-time location and optimization of material handling. The study presents three contributions to the current understanding about DT-based services in SPL, and critical managerial implications.

The first contribution of this paper includes proposing a framework DT-based services for SPL. This study reveals that combining current understanding about the dimensions of DTs and IIoT is essential for providing DT-based services. Importantly, this study provides evidence that stakeholders at different levels of seniority benefit from combining the functionality of DTs and IIoT in SPL. This finding is important as it may clarify the choice of IIoT devices for achieving the benefits of DT-based services in material handling, a situation that is crucial for increasing understanding of DTs in SPL.

The second contribution of this paper constitutes evidence indicating the benefits of DT-based services combining real-time location and optimization in SPL. For example, the results of this study show that applying a dynamic optimization method reduce distance, late deliveries, and makespan in an SPL demonstrator when compared to ad hoc practices. This results is important for two reasons. First, the results show that complying with the objective of not late deliveries requires additional resource. Second, the results provide a schedule distributing tasks for each forklift. Taken together these results present a novel approach that would either be discarded when executing material in an ad hoc manner, or fail to meet the objective of no late deliveries. This finding may be essential for manufacturing companies investigating solutions to a large number of operations, rapid changes of circumstance, and uncertain events in SPL.

The third contribution of this paper is that of DT-based services addressing the concerns of stakeholders in SPL. The findings propose three types of services for each stakeholder including monitoring, prescriptive and predictive DT-based services. This finding may be essential for aligning the activities of stakeholders in SPL and enabling clear and transparent structures for achieving goals.

The results contains practical implications benefiting engineers and managers responsible for improving the delivery of materials and information. This study highlights the need for manufacturing companies for understanding the use of IIoT devices and developing capabilities for applying digital technologies transforming traditional production logistics into smart objects. Managers may be well advised on furthering their knowledge on the five essential components of DTs. Accordingly, this study described the implications of applying IIoT devices, facilitating data connection and storage, and developing virtual production logistics when establishing DT-based services in SPL.

This study includes three limitations. Firstly, communication of devices limits to a laboratory environment. Therefore, future research could develop applications for applying the proposed framework in industrial settings including the use of PROFINET connection. Secondly, this study investigates forklifts exclusively. Future research could analyze additional resource for material handling including conveyor systems, AGVs, or human operators. Thirdly, the results of this study rest on the dataset of a single case. Accordingly, future research could verify the findings by performing a design of experiments.

ACKNOWLEDGMENTS

The authors would like to acknowledge the support of the Swedish Innovation Agency (VINNOVA). This study is part of the Cyber Physical Assembly and Logistics Systems in Global Supply Chains (C-PALS) project. This project is funded under the SMART EUREKA CLUSTER on Advanced Manufacturing program.

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