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A Digital Twin Architecture for Automotive Logistics– An Industry Case Study

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Abstract

The current automotive industry is transitioning from Internal Combustion Engine (ICE) vehicles to Electric Vehicles (EVs), adopting a mixed assembly production approach to respond to fluctuating demand. While mixed assembly production offers the advantages of lower investment costs and flexibility in responding to changing demands, the supply of EV components requires more extensive provisioning compared to ICE vehicle components, potentially leading to unexpected issues such as congestion of transport vehicles. This study proposes a digital twin system architecture that uses Discrete Event Simulation (DES) and Business Intelligence (BI) tools to specifically address logistics challenges. The proposed architecture facilitates real-time, data-driven decision making across three layers; Data source, Simulation, and BI. It was implemented in factories engaged in the mixed assembly production of ICE and EV vehicles. The simulation challenges involve a tier 1 vendor supplying parts to Korean automobile manufacturers that produce both ICE and EV parts. A total of 240 scenarios were created to run the simulations. The deployment of the proposed architecture demonstrates its capability to quickly respond to diverse experimental situations and promptly identify potential issues.

Keywords: Business intelligence, Digital Twin, Electric Vehicle, Inbound Logistics, Simulation

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1. Introduction

With the increasing global emphasis on sustainable development and the reduction of carbon emissions, countries around the world are actively promoting the adoption of Electric Vehicles (EVs) as alternatives to Internal Combustion Engine (ICE) vehicles. As a result, the market share of electric vehicles is on a continuous upward trend. South Korea, a major automotive industry player producing over 3 million vehicles annually, has been expanding its production of electric vehicles since 2011, adopting eco-friendly car policies to achieve carbon neutrality [1]. As seen in **Fig. 1**, the market share of EVs in Korea is increasing significantly each year.

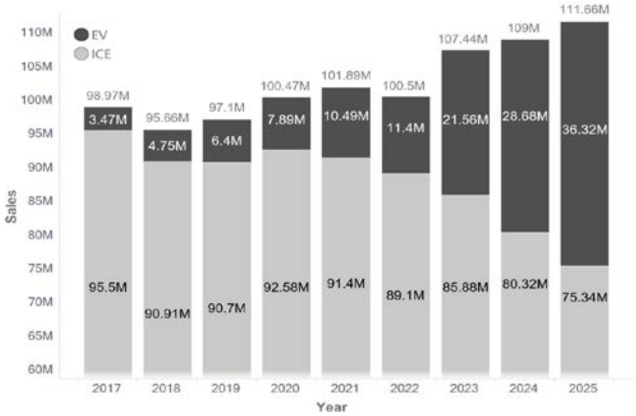

Fig. 1. Percentage of vehicle sales by year

The transition from ICE vehicles to EVs has brought about significant changes in the components that make up vehicles and their manufacturing methods. First, the number of parts used in EVs has decreased by 37% compared to ICE vehicles. Electric motors have replaced the engines in ICE vehicles, leading to a reduction in the number of drivetrain and electronic components. **Table 1** illustrates the characteristics of EV vehicles, which have significantly fewer components compared to ICE vehicles. The number of body and suspension parts for EV is the same as for ICE vehicles. However, in the case of EV, there are no engine parts. As a result, it can be confirmed that the number of parts in EV has significantly decreased compared to ICE vehicles.

Table 1. Comparison of the number of parts for ICE and EV vehicles

Parts	ICE		EV	
	Number of parts	Ratio (%)	Number of parts	Ratio (%)
Engine parts	5,060	23	0	0
Drive & Transfer parts	4,180	19	2,280	19
Body parts	3,330	15	2,880	24
Suspension parts	3,330	15	2,880	24
Other parts	6,160	28	3,960	33
Total	22,060	100	12,000	100

Unexpected logistical issues related to parts supply emerge when mixing the production of ICE vehicles and EVs in existing ICE vehicle factories. Compared to ICE vehicles, EVs have fewer parts, but the size of these parts has increased. For example, the size of the battery pack in an EV is significantly larger than that of an ICE engine. **Fig. 2** illustrates the part size and delivery frequency for ICE and EVs, indicating that the larger size of EV parts reduces the quantity that can be loaded at once, thereby increasing the frequency of deliveries by transport vehicles.

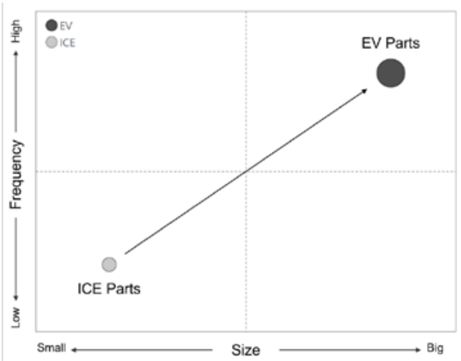

Fig. 2. Changes in EV parts

In a market mixed with ICE vehicles and EVs, predicting the level of new demand growth for EV vehicles is challenging, and changes in the types and sizes of key EV parts make it very difficult to estimate the logistics capacity of supplier factories. Consequently, mixed production will involve the supply of both types of parts, leading to significant fluctuations in logistics traffic for materials and products. Thus, the mixed production of EVs may lead to increased delivery frequencies and issues such as congestion of delivery trucks or a shortage of docks, which were not present when only producing ICE vehicles. Various operational issues related to production and logistics may arise as well.

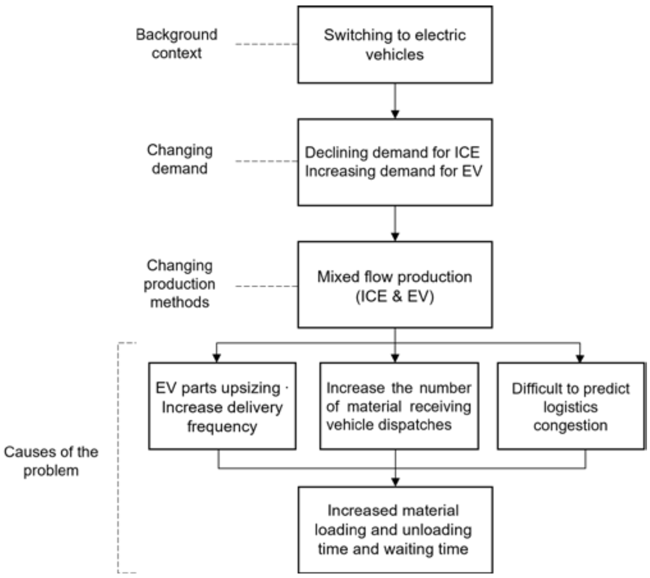

Fig. 3. Background and problem

The problem situation in this study is as follows. 1) It is impossible to predict the logistics flow congestion of material receiving vehicles due to the mixed production of ICE and EV vehicles, 2) As EV parts become larger than ICE parts and the frequency of delivery increases, it becomes difficult to estimate the capacity of logistics resources and the layout of loading and unloading yards suitable to produce EV parts. In **Fig. 3**, we summarize the changes in EV vehicle characteristics and the resulting problem situations in one flow, starting with the transition to EVs, which is the background of the study, and gradually increasing the demand for EVs. It is important to improve the logistics problem because the logistics cost of supplying parts in a mixed automobile production plant accounts for 20-30% of the manufacturing cost.

The digital twin technology, which connects virtual and physical spaces, plays a crucial role in the smart manufacturing industry [2]. However, as the manufacturing process becomes more complex and dynamic due to the diverse needs of customers, a discrepancy arises between the virtual world of the digital twin and the real world, making it challenging to quickly identify and resolve the various problems that occur during manufacturing [3]. This is especially true for logistical operational issues that arise during the transition from ICE vehicles to EVs, where monitoring, analyzing, and simulating real-time operational situations are critical. Despite this, there is a notable lack of research on digital twin system architectures that facilitate these capabilities.

This study aims to address logistic operational challenges by proposing a digital twin system architecture for practical solution. Using Discrete Event Simulation (DES) and Business Intelligence (BI) tools, we present a practical system architecture and that is then implemented and applied in a real-world company. This study was organized as follows. In section 2, we review the existing studies on logistics operations issues in the automotive industry. Section 3 presents a digital twin system architecture designed to address these logistics operations challenges. Section 4 presents a case study where the proposed architecture is applied in a real-world automotive enterprise. Finally, Section 5 outlines the conclusions of the study.

2. Literature Review

In this section, we survey the literature on the logistics, materials, and production complexities that are problematic in the production of automotive components in mixed production and examine the literature on mixed production of ICE components and EV components. As a result, we will list the major papers and identify their contributions and limitations to define the unique and differentiating aspects of this research.

2.1 Related Studies

The impact of complexity on automotive mixed production is analyzed by [4] and it presented a methodology to increase flexibility and efficiency and lower work overload through a strategic approach. A monitoring system with a three-layer network control structure for optimizing material supply in a JIT-based mixed automotive assembly process is designed by [5] and they proposed a method to efficiently supply materials. [6] evaluated the scalability and switch ability of an automotive assembly line in the presence of variant specificity to assemble electric motors and internal combustion engines. A heuristic procedure for flexibility evaluation was then proposed to derive parameters and evaluate change factors based on the manufacturing process to support decision-making on the final assembly line configuration. [7] integrated the complexity level of welding equipment and systems in the mixed assembly process of automobile body and identified the influence of complexity and sensitivity to optimize the process equipment. [8] constructed an integrated logistics model by reducing the outbound logistics time and lead time in the automotive mixed production process and solved the mismatch between production schedule and logistics requirements. [9] defined that the parts supply problem in an automotive mixed production plant is related to the assembly line stations and developed a heuristic solution consisting of two steps to supply parts according to the assembly sequence. [10] developed an approach to allocate manpower during assembly operations to minimize the production cost of a new vehicle model in an automotive mixed production line and presented algorithms to solve the line balancing and vehicle model sequencing problems. A heuristic procedure for a problem of rearrangement in an automotive mixed production line was proposed to find the optimal process conditions according to the production sequence [11]. [12] developed a mathematical model to solve the parts supply problem for automotive mixed assembly process and verified the optimal scheduling combination for material delivery tasks by simulation. [13] organized a simulation and proposed a management system through parameter derivation to improve the parts supply system and manpower planning and balancing in the welding process of an automobile company. **Table 2** summarizes the research contents of the related literature, divided into research fields, algorithms used in the research, whether simulation is used, and whether it is applied to the actual industry, and identifies the logistic scope of the literature that studied the logistics of mixed production.

Table 2. Related research summaries

Related research	A field of study	Development algorithm	What-if simulation	Logistics flow	Industrial applicability
Cao and Zhao 2011 [14]	Inventory	Optimization	X	Operations	O
Golz et al. 2012 [9]	Logistics	Heuristic Algorithm	X	Operations	X
Jin et al. 2008 [8]	Logistics	Optimization	X	Outbound	X
Keckl et al. 2016 [4]	Production process	-	X	-	O
Lafou et al. 2015 [6]	Production process	Heuristic Algorithm	X	-	O
Liu et al. 2017 [7]	Facility	Information entropy theory	X	-	O
Yin et al. 2021 [10]	Woker	Hierarchical Method	X	-	O
Cao and Sun 2019 [11]	Production process	Heuristic Algorithm	X	-	X
Zhou and Zhu 2021 [12]	Logistics	Simulation, Optimization	O	Operations	X
Pereira et al. 2022 [13]	Logistics	Simulation	O	Operations	O

2.2 Limitations of Related Researches

The literature on automotive mixed production processes has mostly focused on processes to optimize production lines [4, 6, 11], and few studies have addressed the logistics challenges of changing mixed production methods. The literature on logistics has either optimized how to move parts and materials within a factory or created outbound logistics plans for just one process [8, 9, 12-14]. It also has the limitation of ignoring current inventory and demand and focusing only on scheduling rules, which does not accurately reflect the current situation.

Due to the dynamic nature and high uncertainty inherent in logistics, traditional scheduling research alone is insufficient to address the complex problems of the real world. While simulation analysis methods offer the advantage of effectively analyzing uncertainty across different scenarios, they are limited by their inability to facilitate real-time decision making. Consequently, digital twin technology, which focuses on supporting real-time decision making, represents a promising solution to overcome these limitations. Despite the active research in digital twins, research specifically aimed at solving logistics operational problems is relatively scarce.

3. Digital Twin Architecture Focused on Logistics Challenges

The digital twin system, which is firstly mentioned in [15], is a real-time decision-making method based on a detailed simulation of reality. Following this, the concept of the digital twin has been expanded to include a digital replica of a manufacturing object, process, or production system that updates in real-time to reflect changes in its physical system [16, 17]. As mentioned in [17], manufacturing logistics are one of the important keywords in digital twin systems [18, 19]. The problem we focus on is the logistical issues that arise during the transition from ICE vehicles to EVs. To address this, the proposed architecture includes three layers that enable optimal real-time decision making by reflecting the dynamic and uncertain characteristics of logistics. The Data Source layer is responsible for the real-time collection, preprocessing, and transmission of data necessary for decision making. The Simulation layer performs simulation analysis that reflects the dynamic and uncertain characteristics of logistics. BI Layer narrows the range of decision scenarios based on real-time monitoring and analysis, reducing analysis time and increasing the real-time nature of decision making. This architecture significantly integrates DES simulation and BI tools to derive optimal alternatives by incorporating discrete event simulation tools that reflect dynamic and uncertain characteristics, and by using BI tools to narrow the scope of extensive simulation analysis. This approach reduces analysis time and enhances the real-time nature of decision making.

3.1 Data Source Layer: Designing a Data Model for Resolving Logistics Issues

The first step is inbound logistics resources and planning data preparation, which is the process of analyzing the requirements to configure the system and processing the input data into the required form. It is an important process that reflects the characteristics of the system to be modeled by organizing input data and output data, which is the basis for modeling.

In order to reflect the situation where materials for internal combustion engine vehicles and electric vehicle parts are mixed and received at the factory, the incoming data is divided into production planning data and logistics resources data by product. The products that make up the data are materials for ICE and EV parts, and the data covers the warehousing process for two years starting in 2023. The resources required include vehicles to bring in materials, forklifts to load and unload materials at the warehouse, and workers at the factory. This study received the necessary data for each resource from the targeted company targeted and organized the meaningful data, and converted it into the data table format used in the logistics simulation. In Table 3, the input data is divided into data target and data variety, and the columns, details, and characteristics of each data are summarized.

Table 3. Input data schema and information

Data target	Data variety	Data column name	Detail
ICE Parts, EV Parts	Production planning	Material code name	ICE/EV material code
		Dispatching group	Group by part type
Parts Storage	Production planning	Waiting area	Parts loading/unloading location
		Waiting capacity	Number of trucks acceptable
Truck	Logistics resource	Truck specifications	Truck type, weight, full length/width
		Shipment capacity	Number of pallets per truck
		Delivery capacity	Number of shipments per day
		Transit waiting time	Loading/Unloading time
Forklift	Logistics resource	Quantity	Number of forklifts
		Speed	Forklift speed
		Efficiency	Forklift operation efficiency
		Transit time	Loading/Unloading time
Worker	Work calendar	Working hours	Working hours, rest hours
		Holiday	A predetermined holiday

In addition, data cleansing is conducted to ensure the accuracy, completeness, and consistency of collected data. Through the data cleansing process, duplicate or incomplete data is removed, and data that does not conform to the specified format is reorganized to improve the quality of the data.

3.2 Simulation Layer: Performing What-if Simulation in Digital Twin Environment for Prediction of Logistics Issues

To forecast inbound logistics operation issues, DES methodology is employed to reflect various resources, their relationships, interactions, constraints. DES simulate events occurring intermittently over time, allowing for the development and analysis of various scenarios, so called What-if, to evaluate system performance and aid in decision making. What-if simulation is a simulation technique that uses scenarios to predict and analyze the possible outcomes of a specific situation or event. It is used to mimic possible future situations and explore their responses and consequences. To do this, multiple scenarios are designed for a specific situation or event. These scenarios are developed by considering the possibilities for different conditions, variables, and input parameters. In this study, three variables, as described in Table 4, were set that can be directly changed according to the situation when performing simulation. By adjusting three manipulated variables, 240 scenarios were generated and three KPIs were defined to evaluate and analyze the optimal scenario.

Table 4. Manipulated variables for What-If simulation

Parameter	Definition
Material management efficiency	It defines the difference in efficiency level of loading/unloading ICE and EV parts, which in turn affects the frequency of transportation.
Number of forklifts	It is the number of forklifts loading/unloading ICE and EV parts. The transit time varies depending on the number of forklifts.
Forklift efficiency	It establishes the efficiency of loading/unloading ICE and EV parts and influences transit time.

3.3 BI Layer: Building BI Environment to Analyze Various Scenarios Based on Key Performance Indicators

The development of various scenarios through What-If simulations has resulted in a significant amount of time required for result analysis. Furthermore, in order to make decisions, representative performance evaluation metrics are needed. In order to systematically analyze extensive data management and real time accumulating simulation result data, it is imperative to establish BI environment. This study designed a BI environment by defining Key Performance Indicators (KPI) based on predefined templates, enabling trend analysis and issue identification.

In this study, three KPIs were defined to evaluate the performance of the implemented model through simulation results. The first is the number of unassigned trucks, which refers to the number of trucks that are assigned after working hours, and the higher the number of unassigned trucks, the more likely it is that there are not enough forklifts to load and unload parts in the factory and the longer the waiting time. The second is the Delivery compliance rate, which is the ratio of the number of trucks actually dispatched to the number of trucks planned in the dispatch schedule. The closer the dispatch adherence rate is to 100%, the more likely it is that all planned dispatches have been made. The third is transit workload, which is calculated as the ratio of the number of hours spent dispatching to the number of hours worked per day. Using these KPIs, we could validate the developed simulator and evaluate the incoming truck dispatch and forklift loading and unloading operations and defined experimental scenarios to address the problematic situations. Table 5 summarizes the meaning of the three KPIs, the calculation formula, and the required data table.

Table 5. Definition of three Key Performance Indicators for validation and forecasting

KPI	Meaning	Calculations	Unit
Number of unassigned trucks	Number of trucks dispatched after working time	–	Number
Delivery compliance rate	Distribution plan execution rate	$\frac{\text{Actual trucks dispatched}}{\text{Planned trucks dispatched}}$	Ratio (%)
Transit workload	Time spent on loading during the working time	$\frac{\text{Sum of transit times}}{\text{Daily working hours}}$	Ratio (%)

3.4 Interface Architecture among Layers

Data source layer prepared the raw data required for modelling as an excel file and built a *MySQL* server to import the raw data into the input data schema. Next, simulation layer connected the sql server to digital twin (*Automod*, *AnyLogic*, *Plant simulation*, etc.) and accessed the input data schema to receive the required data for modelling were executed. To do this, we used ODBC (Open Database Connectivity) to connect input data and digital twin environment. After performing the simulation, BI layer designed the process to upload the resulting data back to the SQL for data analysis and visualization through BI tool (*Tableau*, *Spotfire*, *FineReport*, etc.). Data architecture organization of the simulator is shown in **Fig. 4**.

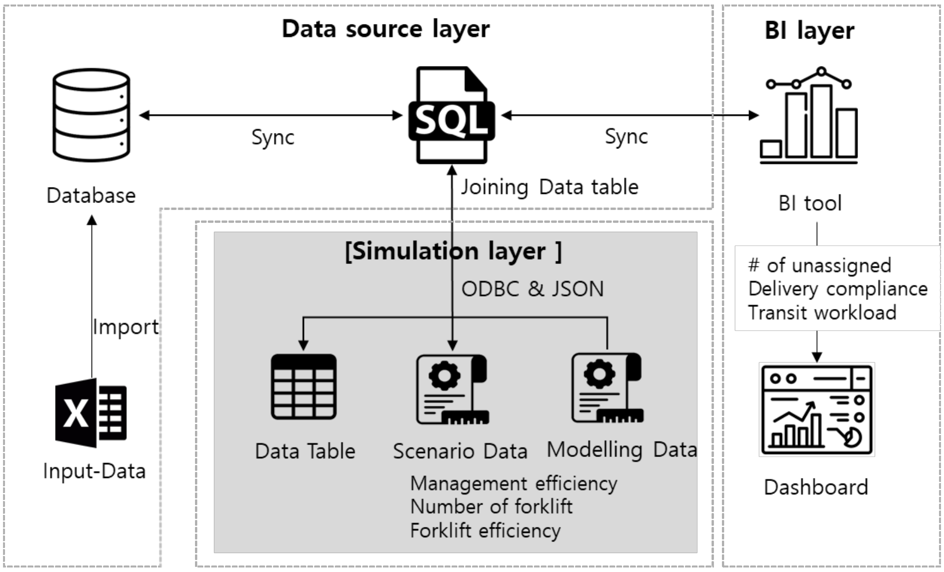

Fig. 4. Proposed system architecture for digital twin environment

4. A Case Study

To validate and assess the feasibility of the proposed methodology, a case study was conducted following four steps; (1) Defining problem situation, (2) Modelling digital twin system architecture, (3) Developing a logistics simulation and generating 240 scenarios, (4) Validating developed what-if scenarios and analyzing forecasting data through BI tools. The case study in this paper is a tier 1 vendor supplying parts to a Korean automobile company that produces a mix of ICE and EV parts. In this study, Siemens' Plant Simulation was utilized in the simulation layer, while TIBCO's Spotfire tool was employed in the BI layer.

4.1 Problem Statement

The monthly changes in the truck shipments for daily parts supply between the years 2023 and 2024 for this company are shown in **Fig. 5**. With the increasing proportion of EV production, the number of shipments for EV parts has increased, while the number of shipments for ICE vehicles has decreased. It is important to note that the total number of shipments has also increased along with the increase in the proportion of electric vehicle production, because EVs require more frequent supplies for the same quantity.

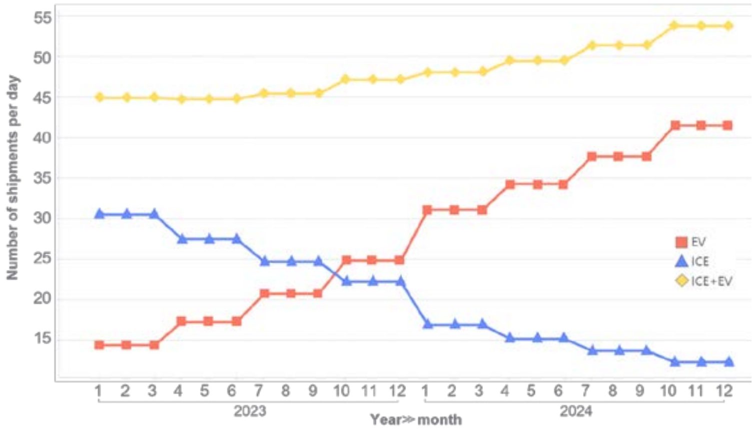

Fig. 5. Changes in shipments of ICE vehicles and EVs by year

The increase in shipments has not merely resulted in an increase in the number of occurrences, but has also caused serious truck congestion in inbound logistics. The layout of the company in this study is shown in **Fig. 6**. When a material receiving truck pulls into the factory entrance, a forklift at the loading dock loads parts into the warehouse. A single truck can unload parts at an unloading dock, and the next truck entering the factory will wait in a waiting area. Only two trucks can wait at the waiting area within the factory, and if the frequency of material arrivals and departures increases and trucks continue to arrive at the factory, they will wait on the public road outside the factory. If the trucks are waiting on the road outside the factory, they will cause traffic congestion and problems for regular vehicles driving on that road. In this study, we model the movement of trucks and the waiting situation inside the factory and derive the problem by observing the actual congestion situation.

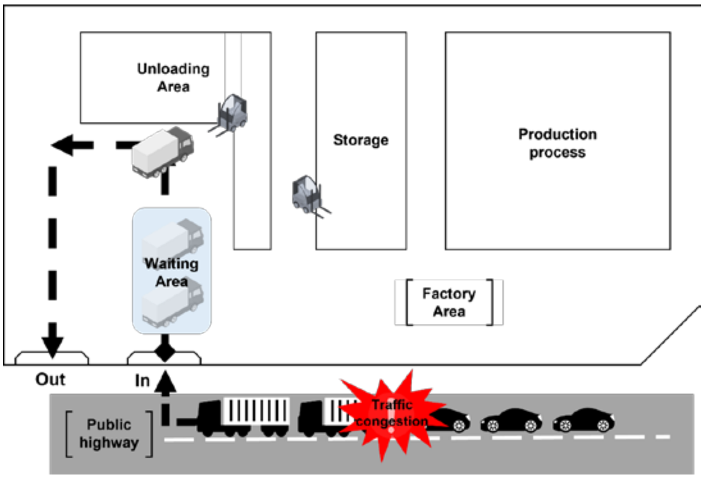

Fig. 6. Inbound logistics layout and problem circumstance

4.2 Establishment of System Architecture

The flow of establishing a distribution plan by running the simulation and distributing trucks by day is summarized in **Fig. 7**. The figure describes the flow in three steps: (1) Data source layer includes the distribution plan and truck capacity information (2) Simulation layer executes the distribution by day, and shows the data used for each process and the data table calculated as a result of the method and algorithm execution. (3) BI layer uses the result data and evaluates the developed 240 scenarios. All information is synchronized in real time by a defined communication protocol, and simulation results are designed to be evaluated with three key performance indicators using a predefined BI template.

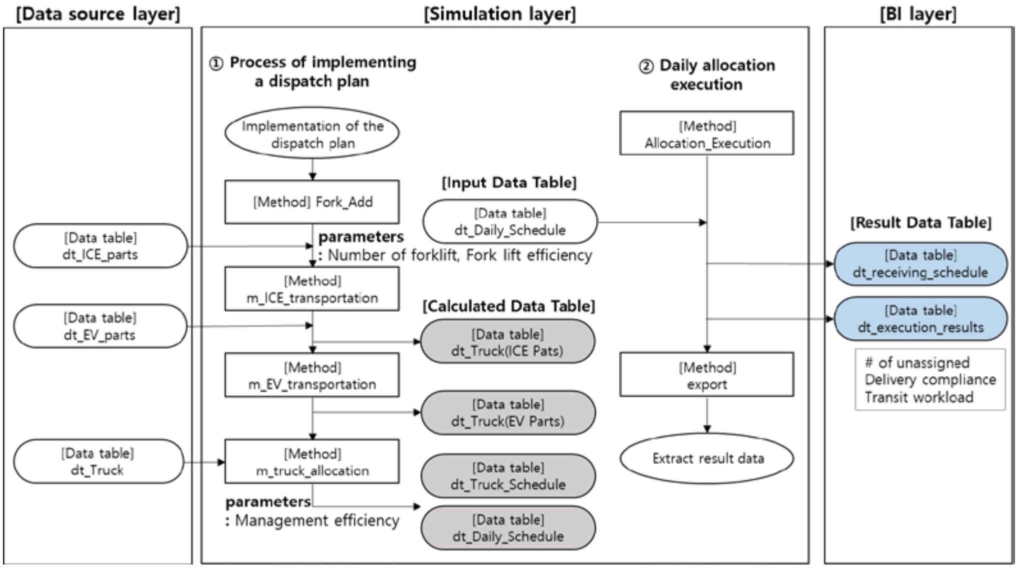

Fig. 7. Data table connection considering proposed architecture

4.3 Development and Execution of Logistics Simulation

This study modelled the logistics planning and truck dispatching algorithm to store the total number of transportation per distribution truck group as well as the parts and quantities that need to be transported in the data table.

Logistics planning operation algorithm designed procedure for calculating the distribution truck group as shown in **Fig. 8**. The distribution group of each part is generated and determines if the sum of the daily transportation counts of parts in the same distribution group is less than the material management capacity factor. If the sum of the number of transports is greater than the capacity factor, then the lower bound of (sum of transports/efficiency factor) is set as the transportation cycle, and if the sum of the number of transports is less than the efficiency factor, then the lower bound of (efficiency factor/transports) is calculated as the transportation cycle. The result is the amount of ICE and EV parts that need to be transported per day through the transportation cycle. Truck dispatching algorithm was executed to calculate the truck dispatch schedule for each day. The dispatch planning algorithm is an algorithm that dispatches vehicles according to the required number of dispatches per day for each ICE and EV part. Through the dispatching algorithm, the truck ID and the number of transportation are identified, and the number of transportations is allocated reversely if the number of transportations required per day is less than 1. The dispatch result data are generated which shows the Id, information, and date of the trucks that need to be dispatched, and the schedule, which summarizes the total number of dispatched trucks. The simulation is performed from the start of the shift at 8:05 and reflects only 9 hours and 20 minutes of work time, excluding breaks and lunch. If a receiving truck is dispatched beyond its shift, it is counted as an un-dispatched truck.

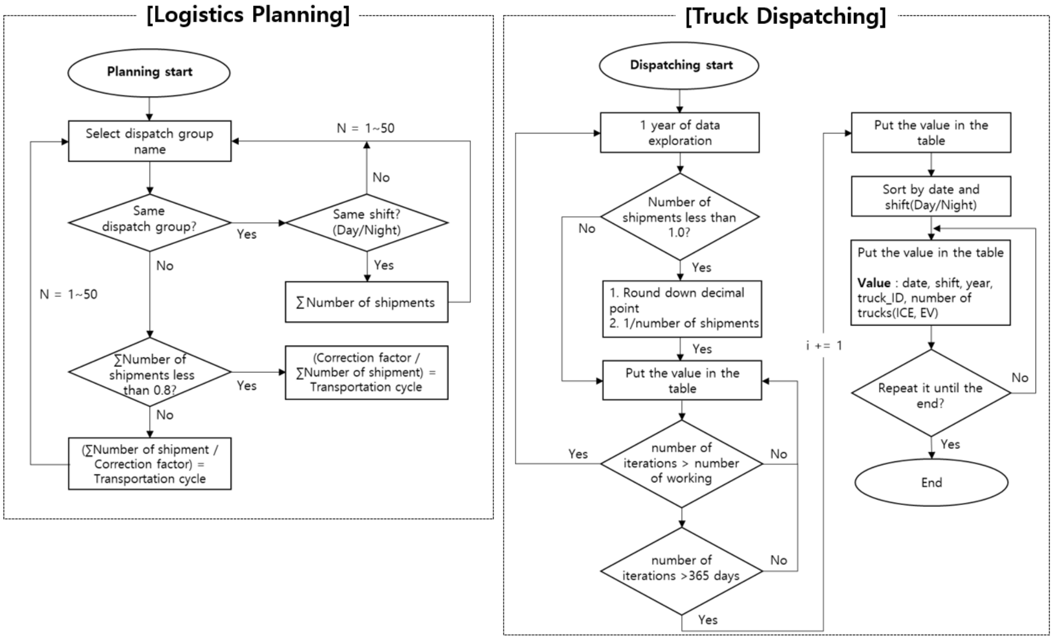

Fig. 8. Logistics planning operation and truck dispatching algorithm

This study constructed a simulation environment based on planning data generated through developed algorithms, defined layouts, and logistics resource quantities. Based on the data, the logistics simulator was configured to reflect the route that trucks carrying parts travel inside the factory and the situation where forklifts move products to the storage area. As shown in **Fig. 9**, the configuration of the logistics simulator is divided into four quadrants to easily identify the necessary methods, data tables, and various resources while performing simulation.

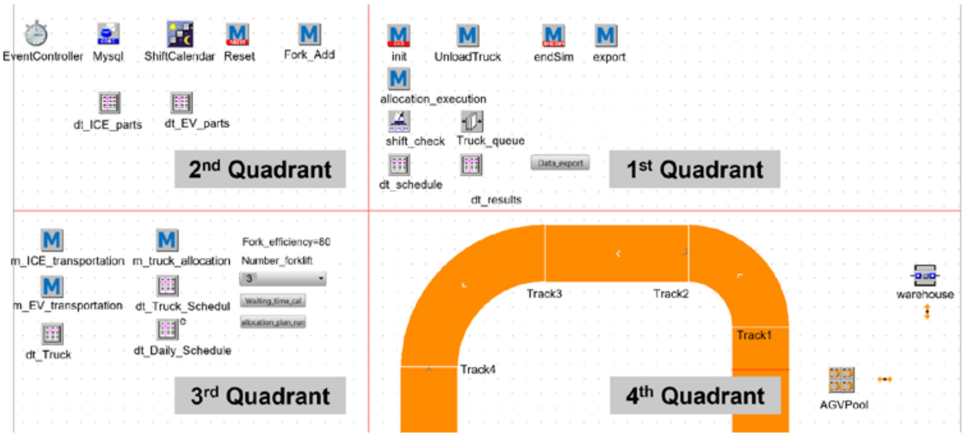

Fig. 9. Logistic simulator development (snapshots from *Plant Simulation*(SIEMENS))

In the first quadrant, there is a data table to record how to execute the distribution of parts receiving trucks by day according to the distribution plan schedule, a data table to record the results of the distribution execution. The second quadrant consists of an event controller that organizes the time flow, MySQL that interfaces input data, data on ICE and EV parts, work calendar, and initialization method, and the third quadrant consists of an algorithm method to calculate the number of parts transportation, a truck distribution planning algorithm, and a data table to record trucks and parts by date. In addition, buttons to select material management efficiency and number of forklifts are included so that the values can be changed as needed to execute the distribution plan. Finally, the fourth quadrant shows the track where the parts receiving trucks move based on the route they enter the factory and move inside, and the place where they wait to unload parts.

This study generated 240 scenarios by adjusting three input parameters. The first parameter is the material management efficiency of the Truck dispatching, which is set to 80% with 1% increments to change to 100% efficiency. The second parameter is the number of forklift resources, which we increased from 1 to 3. We can choose from 1 to 3 depending on the situation, and the time required decreases to 1/(number of forklifts) for each additional forklift. We designed the transportation time to decrease by 1/n for each additional forklift. The third parameter is the forklift efficiency, which we increased from 80% to 5% and set to decrease the transportation time with each increase.

4.4 Validation and Analysis for Data-Driven Decision Making

Validation is a step to check whether the virtual world constructed through simulation modeling and the real world are implemented the same. In addition, in the verification process, the algorithm code is reviewed or debugged to verify whether the simulation model is implemented according to the developer's intention.

To validate that the algorithms developed in the simulation model are implemented accurately, simulations were performed with a single forklift to verify that the trucks are moved according to the distribution plan. We validated that the algorithm is working by checking whether the number of trucks entering, unloading parts, and exiting the factory is the same as the number of trucks distributed on each day in the data table based on the shift schedule. We also verified that the simulator is simulating the real situation by checking the number of trucks distributing ICE and EV parts.

We developed several analysis interfaces (UI) utilizing Spotfire as our BI tool. It takes into account demand data, part size data, as well as data from logistics planning and truck dispatching algorithm modeling simulations. We observed a continuous increase in the number of EV trucks, reaching a higher level of dispatch starting from 2024. We analyzed that the significant increase in the number of EV trucks was attributed to the rise in demand and the increase in part sizes. Meanwhile, the data for ICE trucks showed a consistent decline over time because ICE demand decreases.

To analyze the possibility of the occurrence of problem situations, 240 scenarios are derived by varying three parameters as follows; material management efficiency, number of forklifts, and forklift efficiency. This study conducted data analysis based on KPIs including the number of unassigned trucks and delivery compliance rate, and transit workload. This study created an analysis template based on three parameters to facilitate rapid analysis of the three KPIs.

We analyzed the results of experiments where we varied the number of forklifts from one to three, using it as one of the parameters, with the number of unassigned trucks. Among the 240 scenarios analyzed, it was found that the number of forklifts had the greatest impact on unassigned trucks KPI. As seen in **Fig. 10**, when there was one forklift, an average of 26 trucks remained unassigned per day. However, with two forklifts, unassigned trucks were observed during peak demand periods on specific days. This indicates that having two forklifts can almost meet the demand. Therefore, the case study company concluded that defining the number of forklifts as two is an optimal decision.

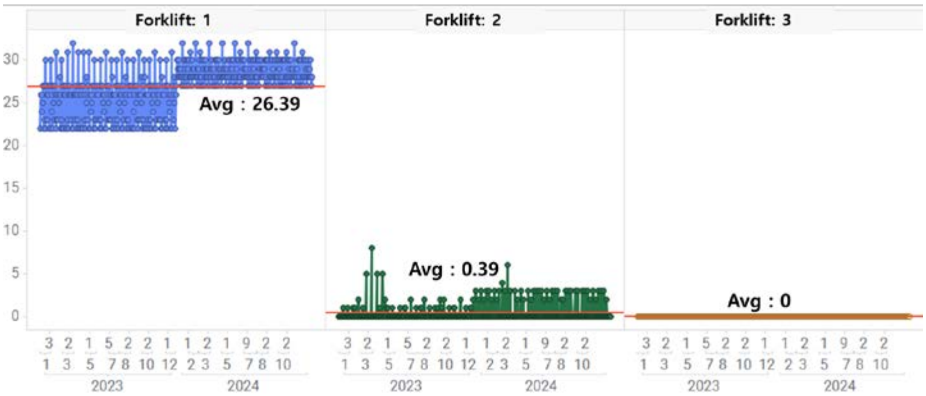

Fig. 10. Number of unassigned trucks by forklift quantity (a snapshot from *Spotfire*(TIBCO))

Next, we analyzed forklift efficiency based on the delivery compliance rate by using BI tool as shown in **Fig. 11**. Forklift efficiency, an indicator influenced by the intensity of workers' work, was analyzed starting from 80% and increasing by 5% increments. As seen in the previous analysis, it was easier to analyze the metric variations when there was only one forklift. Therefore, we defined and proceeded with one forklift for this analysis. With a high number of unassigned trucks, when forklift efficiency was at 80%, the delivery compliance rate was 65%, increasing to 72% when raised to 95%. The rate of increase decreased as the indicator rose from 90% to 95%, and the 100% level was excluded from the analysis as it represented a situation with very high intensity for workers.

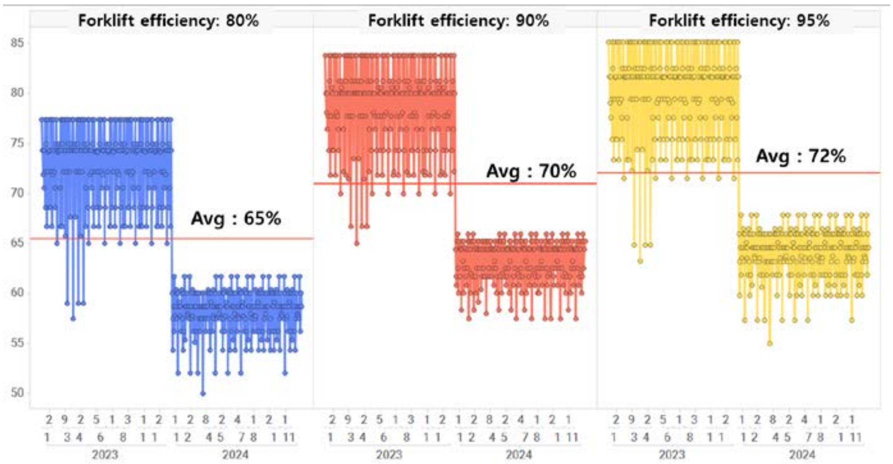

Fig. 11. Delivery compliance rate by forklift efficiency (a snapshot from *Spotfire*(TIBCO))

Lastly, regarding transit workload, it was observed that it consistently remained at 100% across all scenarios, as evidenced by the high occurrence of unassigned trucks and low delivery compliance rates. Therefore, it was analyzed that measures such as reducing demand, extending working hours, or changing shift patterns would need to be implemented.

To analyze the vast amount of data extracted from the simulation, the company integrated a BI tool. Through this, they discovered that designing two forklifts could prevent unassigned trucks. Additionally, establishing work schedules with a 15% increase in worker intensity could minimize job delays.

Monitoring all KPIs through real-time data analysis is essential for swiftly detecting and responding to anomalies across various scenarios, utilizing dashboard-style result analysis templates. This enables real-time data visualization and observation, allowing for rapid identification of problem situations. Additionally, these templates are designed to consolidate information collected from diverse data sources, facilitating efficient decision-making for stakeholders. The **Fig. 12** illustrates the dashboard-style KPI analysis template employed in this study, which allowed for quick analysis of numerous scenarios in a dashboard format. As a result, it enabled the exploration of more scenarios and experiments, granting the capability to swiftly analyze them in a dashboard format.

Fig. 12. Proposed KPI based dashboard template (a snapshot from *Spotfire*(TIBCO))

5. Conclusion and future works

Logistics systems in manufacturing environments are complexly structured. Digital twins have become essential to manage various logistics situations. To expand and operate a digital twin environment for logistics, it is necessary to improve interoperability with various systems and data quality through standardized logistics data. For this purpose, this study aims to establish a digital twin environment for predicting changes in the manufacturing landscape and to build a system for real-time decision-making. Using DES and BI tools, we present a practical system architecture with three layers (Data Source, Simulation, and BI layers). By developing such a standardized structure, it is possible to build a digital twin logistics environment that can respond to changes and expansions in the logistics system. To validate and assess the feasibility of the proposed architecture, a case study for a tier 1 vendor of a Korean automobile company was conducted. In this case study, the electric vehicle hybrid production environment and the digital twin system are defined. Furthermore, 240 scenarios are generated and simulated by a logistic simulation model. These scenarios are analyzed by BI tools with three KPIs for decision making. Through the results of the case study, our suggested architecture demonstrates its capability to quickly respond to diverse situations in the real world.

For future research, this study intends to define the procedures for analyzing the results of the simulation predictions using visualization and BI tools. Furthermore, this study aims to establish a framework for data-driven decision making within the digital twin environment and define a detailed IT structure that facilitates the real time data driven decision.

As a limitation of this study, it should be noted that there is an international standard-based definition for logistics data required to establish a digital twin. The Asset Administration Shell (AAS) is a key data standard and integration model for constructing digital twins in industrial settings. It serves to digitally represent industrial assets in a standardized manner, with each asset having its own digital model known as an Asset Administration Shell. While research on linking product design and manufacturing data is actively underway, there is a lack of research in the logistics domain. Therefore, in future studies, we intend to define logistics-related resources and generated data, and proceed to construct them into an AAS model.

Although this study aimed to integrate simulation with BI tools from a data perspective, it encountered limitations in extending integration to the enterprise information systems. Detailed system architecture designs for integrating with enterprise information systems such as ERP (Enterprise Resource Planning) or MES (Manufacturing Execution System), which manage production lines, will be studied for future development.

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