Smart Warehouse: WMS, AI, IoT and Digital Twin Integration.

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Abstract

In this paper, the development of our innovative smart warehouse system, integrating cutting-edge technologies to optimize warehouse operations was presented. Our solution combines a robust hardware platform with an advanced Warehouse Management System (WMS), Artificial Intelligence (AI), Internet of Things (IoT) and Digital Twin (DT) capabilities. This seamless integration enhances real-time data visibility and improves operational efficiency. By leveraging AI-driven analytics and IoT connectivity, our smart warehouse offers greater accuracy, flexibility, and scalability, setting a new standard for modern supply chain and logistics management. This transformative approach paves the way for the future of automated warehousing.

Key Words: Smart warehouse, IoT, AI, WMS, Logistics, Digital Twin.

1 Introduction

In the early 2020s, the global supply chain underwent transformational changes, driven in particular by the COVID-19 pandemic, which significantly increased the demand for online shopping. This shift challenged both traditional and hybrid logistics companies to adapt, as conventional warehouse management methods and their ability to meet market demands became outdated. The obsolescence of technology and non-standardized infrastructure led to rising maintenance costs, while inefficient picking processes—accounting for 55% of total operating costs [4] —further strained logistics operations. As a result, modernizing logistics activities has become an urgent necessity.

Vietnam, which is a developing country with an average annual e-commerce growth rate of around 18% and a market size expected to reach 26 billion USD by 2024 (recognized by E-Commerce Analytics) as the fastest-growing e-commerce market in the ASEAN region, reflects positive economic trends [20]. However, this rapid growth also increases the demands on supply chain and logistics management. While 52.8% of shippers opt for domestic logistics services [10], logistics costs represent nearly 20.9% of Vietnam's GDP (2022) [25]. This highlights the urgent need to modernize and optimize warehouse systems to boost export competitiveness and strengthen the economy, both for businesses and for Vietnam as a whole.

Warehouses serve as the foundation of logistics systems and play a crucial role in ensuring the efficient movement, storage, and tracking of goods [11]. Modernizing warehouse systems directly translates to improving logistics service quality. The imbalance between investment and operational efficiency in traditional warehouses stems from challenges such as space management, goods handling, poor management practices, and excessive reliance on machinery [21][29]. These warehouses often depend on manual processes that require significant human involvement and lead to high operational costs, slow processing speeds, and reduced accuracy, scalability, and transparency of information [8].

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Emerging Industry 4.0 (I4.0) technologies—such as the IoT, AI, and Machine Learning (ML)—are reshaping warehouse operations by enabling ”smart” warehouses with real-time data collection, resource allocation, and error reduction. For example, Radio Frequency Identification (RFID) systems facilitate automated identification and real-time tracking and reduce costs, and increase efficiency, while Automated Guided Vehicles (AGVs) enhance order picking and batch processing for operational optimization [17]. In addition, technologies such as IoT, Big Data, and Cloud Servers play a crucial role in the shift toward Smart Warehouses [8][1]. IoT technologies, including QR and RFID applications, allow businesses to monitor, trace, and update large volumes of goods data in real-time [14][2]. It enables rapid responses to market fluctuations and saves 80-99% of processing time and boosts operational efficiency by up to 91% through cross-docking [15]. Furthermore, the strong growth potential of AI, predicted to contribute a 1.2% increase to GDP annually [18], makes Big Data the backbone of advanced deep learning applications, which help identify trends and issues early, thereby enhancing productivity and management efficiency [7][23].

Despite these advancements, several challenges remain including high implementation costs, data security concerns, training requirements, and infrastructure upgrades—all of which create significant barriers, especially for small and medium-sized enterprises (SMEs) [4][28]. Case studies further highlight additional obstacles, such as Sri Lanka’s slow adoption of AI due to limited technological knowledge and resource delays [5]. These issues are commonly encountered in research related to information and communication technology (ICT) applications in warehouse management, alongside limitations in experimental environments.

This paper aims to provide deeper insights into the value of applying AI, IoT, and Digital Twin (DT) technologies to electronic warehouse management systems (E-WMS) through the Smart Warehouse (SWH) model, developed by our center at a 1:10 scale compared to real warehouse systems. By leveraging digitalization, data collection, and real-time analytics, this model enhances remote management capabilities and improves supply chain responsiveness to fluctuations. It also supports decision-making and management strategies with optimized costs and increased operational efficiency.

2 Literature Review

An early demo of ChatGPT was released at the end of 2022 bringing the definition of “AI” closer to the general public. However, applied AI research in real life was earlier than that a long time ago, such as:

- **Education**: AI-powered tutoring applications that support individual learning. For example, “ELSA Speak” uses AI to teach and correct English pronunciation errors.
- **Aviation**: AI assists in pilot training through simulation tools and tactical decision-making.
- **Financial Security**: Banks use AI for algorithmic trading and enable fast and efficient transactions without human intervention.
- **Healthcare**: Computer vision is used to detect abnormalities in the body, such as deformities or cancer, through imaging.
- **Personal Use**: Technology companies equip virtual assistants powered by AI, like Siri on iOS and Google Assistant on smartphones, to help users manage finances and access information more easily.

AI applications for warehouse management have been explored for quite some time. Due to some limitations in technology and infrastructure, it wasn’t until Industry 4.0 was fully developed, with advances in IoT enabling faster and easier data collection and analysis, that the application of AI in warehouse systems began to accelerate. Additionally, the impact of the COVID-19 pandemic on the supply chain, causing a shortage of human resources, further accelerated this process to modernize warehouses and address human limitations.

Modernizing warehouse systems is now driven not only by economic efficiency and operational performance but also by the demand for sustainable logistics and by reducing environmental impact with strategies aimed at achieving Net Zero globally. JD.com serves as an example of the effectiveness that Industry 4.0 technologies bring, integrating AI solutions and clean energy, allowing for same-day or next-day deliveries while reducing carbon emissions. Similarly, Alibaba’s Cainiao warehouse powered by AI in Tianjin has reduced human labor by 70% and increased speed and efficiency. Amazon uses AGVs and AI to optimize demand forecasting, enable same-day deliveries, and drive revenue growth [12].

For e-commerce warehouses, there are technical requirements to operate 24/7 to keep up with rapid delivery demands. Before delving deeper into the technologies explored by the group when building SWH at the center for modernization and AI application in E-WMS, the group will first present the basic operational processes of an optimized warehouse, which include:

1. **Receiving Goods**: This is the first and crucial step in warehouse management, where the quantity and condition of the goods must be controlled to match the delivery time. [4][30]
2. **Storage**: The process of placing goods in suitable storage locations helps optimize storage space and retrieval costs. [4][30]
3. **Order Picking**: The activity of collecting goods in the warehouse to deliver them to consumers. [4][30]

The receiving process is crucial for businesses as it allows them to assess the condition of products before storing them, and enables the identification of defective products and avoids responsibility for them. The storage method and location of goods play an equally significant role, as an efficient management system that allows for easy retrieval can help businesses optimize transportation, storage costs, and order search. Thus, it enhances management performance. Finally, during the order picking process, based on the recorded information, orders are gathered at a consolidation point before being shipped to customers that account for up to 55% of the total operational costs of a warehouse [4]. Therefore, selecting appropriate processes, technologies for retrieval, and management systems will enable the creation of a smart warehouse and reduce substantial costs while increasing efficiency and customer satisfaction, which in turn enhances the competitiveness of the business.

In addition to building a WMS to standardize operational procedures, smart warehouse systems utilizing ICT, with the ability to link through IoT and Cyber-Physical Systems (CPS), not only facilitate the coordination and synchronization of processes but also create added value through real-time data processing [29][13][24]. By promoting automation with modern robots such as AGVs [24], and utilizing Automated Storage and Retrieval Systems (AS/RS) [11] the transportation and storage stages, the system enhances efficiency. The use of RFID/Barcode systems, synchronized with WMS, helps identify, track, and transmit information within the warehouse. Furthermore, AI and Digital Twin applications, in addition to supporting decision-making from data analysis [4][5][27][19], also help address challenges such as Storage Location Assignment Problems (SLAP), Order Picking Problems (OPP) [6], and the development of Engineer-To-Order (ETO) strategies [16]. This reduces manual errors, supports more effective and accurate transportation, storage, and order picking, minimizes operational costs, increases business competitiveness, and enhances customer satisfaction.

Based on the analysis and synthesis from **Table 1**, this serves as the foundational base to help the team begin the project of building a SWH integrated with ICT and automation, based on previous ideas, with a focus on smoothly integrating highly adaptable technologies such as IoT, AI, and DT into the SWH warehouse model. By developing AGVs for transportation within the warehouse, implementing RFID in management and data retrieval, and building CPS along with a database system to monitor and update in real-time across multiple platforms. This research seeks to explore in more depth the potential that Reinforcement Learning (RL) offers for optimizing storage location decisions from equipment and aim to reduce energy consumption and equipment depreciation. Additionally, the research will look into the development of a DT model to support the Engineer-To-Order (ETO) process for the warehouse, create a flexible warehouse environment, remove the limitations of management analytics, and enhance creativity and adaptability to new global trends.

3 Methodology

3.1 Hardware Requirements

3.1.1 Radio Frequency Identification - RFID

The RFID reader/writer ANT 513, which operates at a high frequency of 13.56 MHz and complies with the ISO 15693 standard, is utilized. This device supports a maximum read/write range of 60 mm. It covers both the front and sides and makes it ideal for precise object identification in Smart Warehouse systems.

To track the position of pallets in the SWH, RFID tags are attached to each pallet. Eight ANT 513 RFID readers are used for inbound logistics management: one at the import gate for tag encoding and seven positioned along the inbound conveyor. The RFID writer retrieves optimized ID codes from the E-WMS, based on factors such as weight and storage duration. The RFID readers at each station then verify the tag information and direct the pallets to the optimized storage cells. This allows users to track the entire storage process, improving accuracy, enhancing management efficiency, and reducing operational errors.

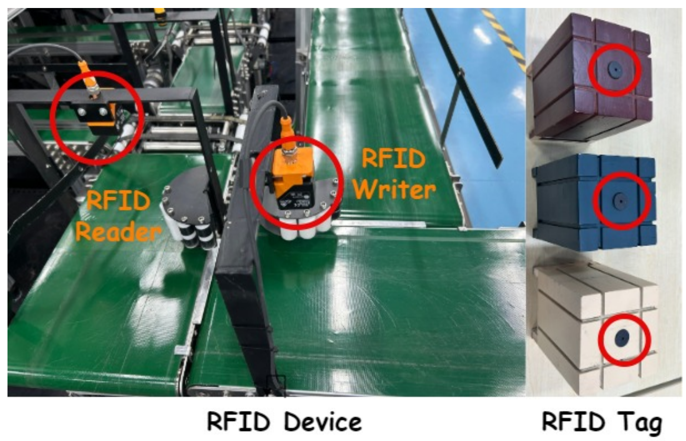

Figure 1: RFID ANT 513 Device and RFID Tag.

3.1.2 Navigation Conveyor System

The navigation conveyor system is used to accurately determine the position of the pallet during the inbound and outbound processes, helping to prevent unnecessary errors. Infrared sensors play a critical role in detecting, tracking, and locating pallets on conveyors, ensuring precise positioning at RFID encoding areas.

During the process of determining the location of goods at each station, the system of navigation conveyors receives signals from optical sensors and RFID data to navigate the goods to the correct station. When pallets are transferred to the inbound conveyor, the infrared sensors halt the navigation conveyor system mechanisms and signal AGVs to retrieve the pallets.

Digital Fiber Optical Sensors are installed on AGVs to ensure precise management of goods handling in SWH. They detect

Table 1: List of technologies referenced in warehouses

Technology	Applications	Key Benefits	Examples	Citations
Autonomous Robots	Loading, unloading, and packaging tasks	Reduced labor costs, improved safety, and operational efficiency	Amazon, JD.com, Alibaba, Ocado	[29][3]
RFID	Real-time inventory tracking and tracing	Enhanced traceability and data accuracy	Coca-Cola's inventory systems	[6]
IoT	Connecting devices and data sharing across logistics nodes	Real-time monitoring and automation	IoT-enabled smart warehouses	[24][6]
AI	Demand prediction, anomaly detection, operational optimization	Cost reduction, improved accuracy, sustainable practices	Amazon: Same-day delivery; Alibaba: 70% labor reduction in **Cainiao** warehouse	[5][9]
Computer Vision	Inventory monitoring and material handling	Increased precision and speed	JD.com, Amazon	[29][5]
Cloud Computing	Hosting WMS and real-time data access	Scalability, accessibility, and cost savings	AWS, Firebase, Auto-Identify Technology (AID)	[8]
CPS	Real-time integration of physical and computational systems	Enhancing decision-making and operational synchronization	Integrated robotics and IoT systems in logistics	[24]
Digital Twin	Research and development to address ETO challenges	Improving supply chain visibility and predictive maintenance	Focchi's warehouse	[16]

pallets, identify empty positions, support AGVs' autonomous operations, and reduce dependency on human intervention.

3.1.3 AGV System

The smart warehouse model system consists of seven AGVs, designed on a 1:10 scale. At each station, an AGV system is responsible for transporting goods to racks that can store up to 196 slots at the same time (1372 slots across 7 stations).

The standard pallet size is designed at a ratio of 1:10 of real pallets, measuring 120mm x 120mm x 175mm, with a maximum delivery weight of 1.5 kg. Each slot in the rack, designed with dimensions of 120mm x 120mm x 300mm, has a load capacity of 3 kg (1.5 x 2 for safety factor).

The AGV dimensions are 858 mm x 158 mm x 1957 mm (LxWxH). The operating range of the AGV is defined by its movement on three axes: - X-axis: -144mm to 2280mm - Y-axis: -150mm to 1240mm - Z-axis: -165mm to 165mm

Figure 2: The design of storage racks and AGV system.

3.2 Software Design

The primary activities in a warehouse system include identifying and receiving orders, counting product quantities, recording storage locations, and delivering goods to the correct cells. With modern technologies, smart warehouses provide enhanced capabilities for monitoring and managing goods more accurately and efficiently than traditional warehouses. Based on the generalized model in Fig. 3, the components are as follows:

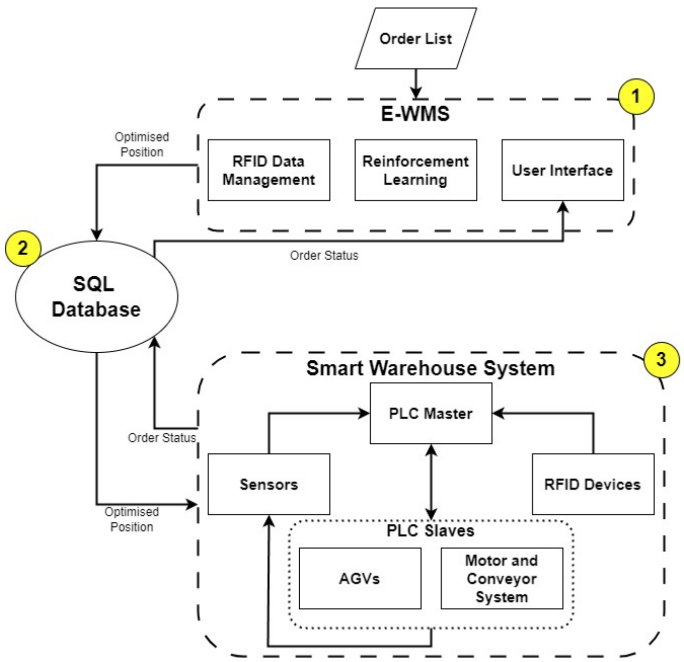

Figure 3: Workflow diagram of the Smart Warehouse.

(1) The E-WMS is the central system for managing and organizing order lists, which can be input manually or provided via Excel files. It optimizes storage locations and assigns RFID tags to orders. Additionally, it serves as the main interface for displaying data, including product quantities (inbound and outbound), available storage slots, and more [22].

- The system incorporates Reinforcement Learning (RL) algorithms to optimize pallet positioning in the warehouse. This optimization minimizes spatial and energy consumption by providing the most efficient cell and path for automated AGVs. RL focuses on long-term reward-based decision-making.
- Deep Q-Learning (DQN), a type of reinforcement learning, leverages deep neural networks (DNNs) to predict values and address large-scale problems [26]:

$$Q(s,a) = R(s,a) + \gamma \sum_{s'} P(s,a,s') \max_{a'} Q(s',a') \quad (1)$$

- The AI model is trained using three main input datasets: weight, import/export dates, and frequency of import/export for each type of product. In the enhanced E-WMS, the environment is the warehouse with a fixed storage space, the agent is the AGV, and the state is the AGV's current position with the reward of that position. The pallet information (weight, import/export dates, frequency) also serves as the policy for evaluating the algorithm.
  - The AGV's current position.
  - A list of occupied and available storage slots
  - Pallet information (weight, import/export dates, frequency) which also serves as the input data for the algorithm.

Actions a involve the AGV moving pallets to an appropriate location. Rewards r evaluate the efficiency of these actions: storing a pallet in the correct position yields a high reward, while incorrect actions result in lower rewards (Fig. 4).

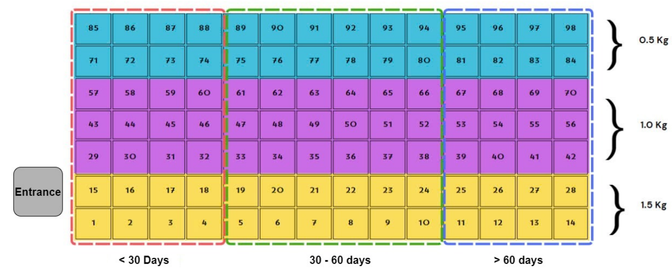

Figure 4: Integration of AI models into Warehouses.

(2) SQL serves as the database system for processing and storing all general information in the system which is a crucial node for data exchange between the WMS and the automated support systems.

(3) PLC Master: The PLC Master acts as the central brain of the automated support system. It processes data from the E-WMS via SQL, sends execution requests to subsystems (e.g., AGVs, conveyors, and RFID), and updates system states back to the WMS.

The E-WMS system manages and optimizes storage locations by analyzing order data (via Excel file or manual input) and using AI algorithms to determine optimal pallet positions based on storage time and available slots. SQL database stores and exchanges real-time order and warehouse status data between the E-WMS and the SWH systems. The PLC Master acts as the central controller and processes data from E-WMS and the SWH systems to navigate AGVs and conveyors. RFID readers and sensors continuously track pallet locations, while PLC Slaves execute actions like transporting pallets according to the orders from the PLC Master.

3.3 Calculation of Travel Time and Energy Consumption for AGVs

To research the performance of smart warehouses before and after AI integration, equations (2) and (3) were developed based on analyses of the collected and measured dataset.

The travel time of the AGV is calculated from the "Entrance" position to the starting position of the warehouse, measured as 2.5 seconds with an energy consumption of 0.319 W·s.

The movement speed and idle power consumption of the motor along each axis are:

- X-axis: Speed = 500 mm/s, Idle power consumption $P_x = 0.087$ W
- Y-axis: Speed = 350 mm/s, Idle power consumption $P_y = 0.058$ W

The time required for movement along each axis is calculated using the formula $t = \frac{s}{v}$:

- Movement time for each grid cell along the x-axis (row):

$$t_x = 0.4 \text{ s} \tag{2}$$

- Movement time for each grid cell along the y-axis (column):

$$t_y = 0.86 \text{ s} \tag{3}$$

Since the distance from the "Entrance" to the starting position is equivalent to the first three rows of the first column (0.8 m × 0.6 m), and the starting time is 2.5 s, the total travel time for one grid cell is calculated as follows:

$$t = 2.5 + \max(t_x(x-1), t_y(y-3), 0) \quad \text{(s)} \tag{4}$$

The energy consumption for each pallet position is influenced by the travel time along each axis (x, y), the weight m, and the energy coefficient a. The formula is as follows:

$$A = 0.319 + (t_x \cdot x)P_x + (t_y \cdot y)P_y + m \cdot t \cdot a \quad \text{(W·s)} \tag{5}$$

Where:

- a: Coefficient of increased motor power consumption for carrying loads (varies depending on motor type).
- m: Weight of each pallet, classified into three groups with coefficients of 0.5, 1, and 1.5, used to calculate the load energy consumption.

3.4 Mobile Application Workflow in the Smart Warehouse System

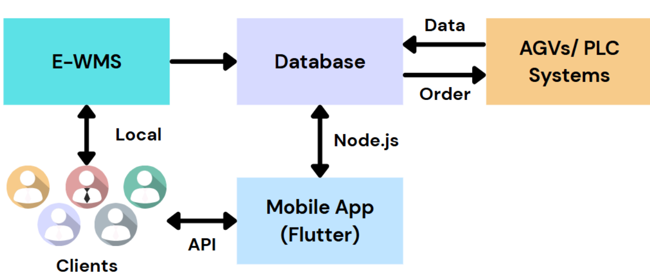

Figure 5: The flow of mobile application.

Current Logistics management services focus on improving user experience and increasing information reliability. With the advantages of applying digitalization and CIT in warehouse data management through E-WMS and Database - these are the advantages that SWH can bring to improve user experience. A mobile platform developed using Flutter is integrated into the SWH system to help Customers access real-time information through APIs provided by the Node.js-based backend service. Figure 5 is as follows:

[1] **Users initiate tasks via E-WMS:** Operations such as inventory requests and order creation are performed through desktop terminals or devices within the local network.

[2] **E-WMS stores data in the central database:** Operational data such as order status and product movement are stored and retrieved from the centralized database.

[3] **Node.js handles real-time data synchronization:** A backend service built with Node.js connects the database to the mobile application via RESTful APIs, supporting queries and user authentication.

[4] **Flutter provides a cross-platform mobile interface:** Users can access key functions like task reception, order tracking, QR/barcode scanning, and task status updates through the mobile app.

[5] **Database communicates with AGV/PLC systems:** Order details are sent to AGVs/PLCs for execution, and feedback such as completion status and location is returned.

[6] **Feedback is synchronized with the mobile app:** Updates from AGV/PLC systems are recorded in the database and reflected immediately in the mobile interface via Node.js.

[7] **Offline support and automatic synchronization:** The app caches data when offline and automatically syncs it to the central database once the connection is restored.

3.5 Digital Twin Integration for Engineer-To-Order Operations

Besides offering strong data accessibility, warehouse digitalization holds significant potential in predictive analytics and strategic decision-making through the development of a Digital Twin model for the Smart Warehouse (SWH).

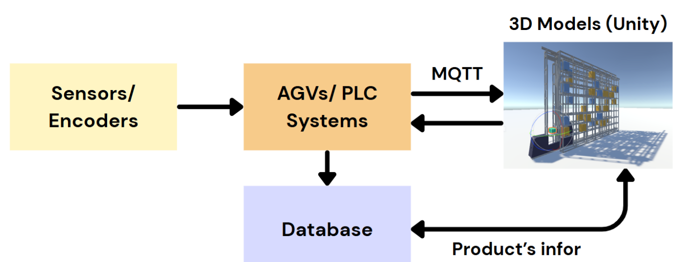

Figure 6: Digital Twin data transmission flow.

To support real-time visualization and Engineer-to-Order (ETO) workflows, a Digital Twin architecture has been implemented in the SWH. The overall data flow and system integration are illustrated in Fig. 6.

[1] **Sensor and encoder data collection:** The physical warehouse is equipped with sensors and encoders attached to AGVs and machinery. These devices collect real-time data such as position, velocity, and operational status.

[2] **AGV/PLC system coordination:** Raw sensor data is transmitted to AGV/PLC controllers. These systems

process the data to make motion control decisions and execute automated handling tasks—forming the key interface between the physical and digital domains.

[3] Real-time synchronization via MQTT: To enable lightweight, low-latency communication between physical systems and the virtual environment, MQTT (Message Queuing Telemetry Transport) is used. It ensures efficient and reliable telemetry data transfer from AGV/PLC to the Unity-based Digital Twin.

[4] 3D visualization in Unity: A virtual warehouse environment is developed in Unity, enabling real-time visualization of warehouse operations. Through MQTT, the 3D models dynamically reflect the current state of physical systems, including product positions, AGV movements, and activity flows—forming a fully synchronized Digital Twin.

[5] Database integration and product mapping: In addition to telemetry data, product-specific information—such as SKU codes, order IDs, and storage locations—is retrieved from the database. This data is used to annotate the 3D models, providing contextual insights for warehouse operators and planners.

[6] Support for Engineer-to-Order (ETO) operations: The Digital Twin offers an interactive interface that supports ETO operations by enabling real-time tracking of custom orders, verifying product routing, and ensuring configurations meet customer-specific requirements. Engineers can simulate logistics scenarios, monitor performance, and instantly adjust control parameters within the virtual model—shortening the feedback loop between design and execution.

This Digital Twin framework enhances monitoring and decision-making, bridging the gap between the physical warehouse and digital control systems, and supporting adaptive smart warehouse management tailored to ETO scenarios.

4 Results and Discussion

Our warehouse system significantly reduces energy consumption by nearly 25% and improves overall operational efficiency by cutting travel time by 15%. Testing on 98 warehouse positions demonstrates the superior effectiveness of this approach compared to traditional management processes and verifies the feasibility of AI technology in warehouse management (Fig. 7).

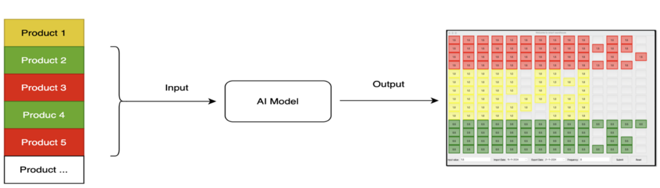

Figure 7: Integration of AI models into Warehouses.

To compare the efficiency of SWH, E-WMS with AI has proven to be more efficient in warehouse management than the previous version which used a traditional algorithm without RL, as evidenced by a depreciation comparison after one week between the two solutions. According to the data, energy consumption and travel time have decreased significantly compared to traditional methods. Travel time was reduced by nearly 10 seconds (approximately 14%), travel energy consumption decreased by 1.02 (W.s) (10.3%), and load energy consumption dropped by 30% during pallet transport. After the R&D phase, the Mobile application has successfully implemented basic monitoring and control features with a detailed interface as shown in Fig. 8.

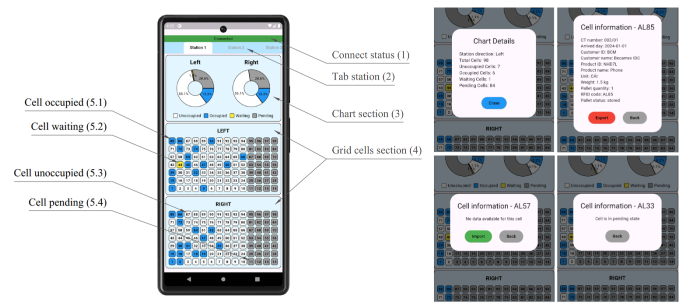

Figure 8: Mobile application for SWH.

1. Connect status: Displays the application's connection status with the server.
2. Tab station: Allows switching between dashboards for 7 stations.
3. Chart section: Displays charts to manage the status and quantity of cells in each station.
4. Grid cells section: Shows the grid of cells within a station for interaction.
5. Cell status:
   5.1 Green indicates a cell containing goods.
   5.2 Yellow indicates a cell in the process of loading or unloading goods.
   5.3 White indicates an empty cell.
   5.4 Gray indicates a pending cell status.

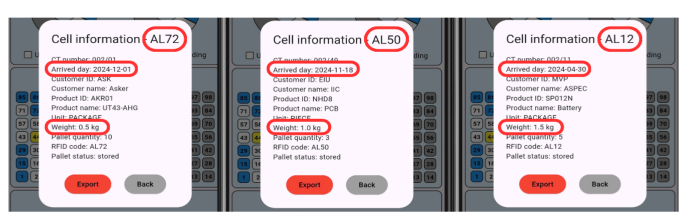

Figure 9: Optimized pallet location information by AI.

In addition to information updated from the database regarding detailed inventory and current locations, Fig. 9 illustrates that the AI model has achieved the projected arrangement strategy as shown in Fig. 4. Pallets are allocated based on designed levels of storage time (less than 30 days, from 31 to 60 days, and over 60 days) and weight categories (0.5 kg, 1 kg, 1.5 kg).

Figure 10: Smart Warehouse after AI and IoT integration.

The integration of AI into the warehouse model has been evaluated using key metrics:

- Import time for the nearest pallet (01): 22s, and the farthest pallet (98): 35s.
- Export time for the nearest pallet (01): 25s, and the farthest pallet (98): 38s.
- Conveyor time for the nearest station (G07): 18s, and the farthest station (A01): 53s.

Compared to traditional warehouse systems, the smart warehouse demonstrates significant efficiency improvements in order processing, from retrieval to transportation (Fig. 10). By optimizing pallet allocation to positions, the system saves energy across all stations, ensures more balanced distribution, reduces excessive equipment operation, and enhances economic benefits.

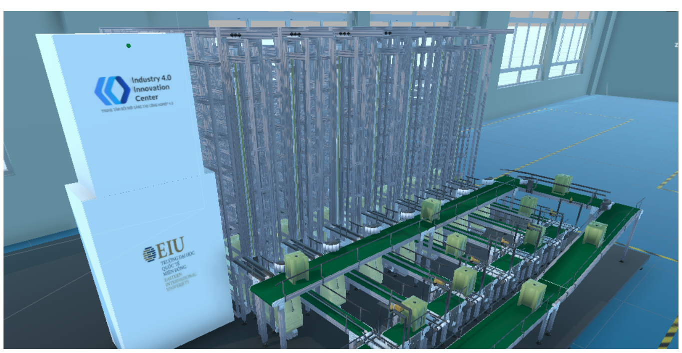

Figure 11: Digital Twin Model of SWH in Unity.

Currently, this DT model has successfully received data in parallel with the SWH and has successfully simulated the movement of AGVs within the SWH (Fig. 11). It can also communicate with the AI-integrated WMS. In the future, the team will collect additional data from sensors and databases to further refine the model and support the development of Engineer-To-Order (ETO) for AI specifically tailored to the SWH, as well as management applications related to energy and risk management.

Limitation:

The current implementation is limited to a 1:10 scale prototype, which does not fully capture the complexity and challenges of deploying and operating such systems in real warehouse environments. Moreover, the machine learning model is currently constrained by a limited dataset, which indicates significant potential for further optimization of both the model architecture and control policies. To fully evaluate the impact of integrating WMS, IoT, AI, and a dynamic Digital Twin in real-world scenarios, substantial infrastructure—including RFID systems, AGVs, IoT devices, and Computer Information Technology (CIT) platforms—is required. This poses challenges in terms of time and cost, particularly for small and medium-sized enterprises (SMEs). A complete transformation would demand a progressive digitalization process, moving from WMS-based workflows to semi-automated or automated systems, followed by the integration of CIT/IoT technologies, and eventually achieving full DT implementation.

Future works:

In the near future, the research team aims to expand the capabilities of the DT environment to support predictive maintenance (PM) and testing solutions. By developing comprehensive testing tools within the DT framework, it will be possible to simulate and evaluate various warehouse layout strategies and policies, that enable the identification of the most effective machine learning models. This will also facilitate the collection of valuable operational data to support the development of predictive maintenance algorithms.

Additionally, the mobile application will be further enhanced with advanced security features and deployed in real warehouse environments to assess its effectiveness and impact on warehouse management performance. Future versions of the app will also include integrated chatbot functionalities to improve user interaction and service quality in inventory and workflow management.

5 Conclusions

In addition to the proven benefits in operational efficiencies—such as faster inbound and outbound processes—and energy optimization—through reduced consumption and minimized machinery depreciation—the integration of RFID, AI, DT and mobile applications with the E-WMS software, coupled with synchronization with the database system, establishes a comprehensive and intelligent seamless process. The SWH is one of steps for us to shift the focus from human-intensive to technology-intensive. It emphasizes strategic management and sustainable development.

The proposed solution represents a step toward the advancement of Industry 5.0, with a focus on sustainable energy practices and a more human-centric approach to technological development. Leveraging the current capabilities of modern sensor systems and database infrastructures, the potential of SWHs extends into predictive maintenance and digital twin technologies. These innovations enable the identification and mitigation of potential issues before they arise, facilitate improved risk management and proactive responses to market changes through predictive scenario modeling.

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