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Toward Industry 5.0: An IoT-Enabled Digital Twin for Joint Sustainability and Resilience Optimization in Automated Warehouses

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Abstract

As e-commerce expands, automated e-fulfilment centers are important for fast and dependable delivery of orders placed online. Robotic equipment performs most of the operational work in these centers, supported by Internet of Things (IoT) that provide real-time operational data. Although these innovations show the principles of Industry 4.0, the transition to Industry 5.0 creates an economic trade-off between resilience and sustainability for the increasing demand for both. The main challenge is to reduce energy use without compromising the ability to manage demand fluctuations. Existing research has typically focused on sustainability or resilience by improving individual processes in isolation, which limits trade-off of resources usage and performance, as well as the interconnected nature of logistic operations. To respond to this challenge, the study proposes a Digital Twin for Joint Sustainability and Resilience Optimization (DT-JSRO) model to help in decision making coupled sustainability-resilience optimization. The DT-JSRO model lets managers run scenarios for performance evaluation in sustainability and resilience while guiding users on the best resource allocation strategies. A simulation experiment proved the feasibility and effectiveness of the proposed approach. The model simulates different operational scenarios to produce the best resource allocation strategies that can assist practitioners based on practical priorities, including solely sustainability, resilience or jointly optimizing the two when needed.

Keywords: IoT; digital twin; Industry 5.0; sustainable automated warehouse; real-time optimization

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1. Introduction

Due to the highly digitized world, e-commerce has become a worldwide phenomenon where online retail has proved to be of great competitive advantage. Global online retail revenue was almost six trillion U.S. dollars in 2024 [1]. According to projections, this number is set to increase by 31 percent in a few years and nearly reach eight trillion dollars by 2028 [1]. Rather than a trip to the store, customers expect their orders to be delivered to their home. Buying patterns are shifting as people find it easy to shop online [2,3].

Due to the changing trends of shopping among the consumers, there has been a marked increase in online orders. This has put considerable pressure on distribution centers in order fulfillment services. Furthermore, it is far more complicated to handle these e-orders than retail orders. The traditional order mainly consists of a small number of SKUs in a bulk order for routine stock replenishment. On the other hand, e-commerce orders are known to be more wide-ranging in delivery locations and larger in variety of SKUs with a small number of each SKU [4]. As a result, distribution centers have to process huge amounts of e-commerce orders on a tight time schedule. To meet these challenges, such distribution centers are increasingly investing in automated warehouses with high-level infrastructures [5,6].

Automated warehouses utilize advanced automated technology and systems to perform storage, picking, and packing activities with minimal or no human intervention. Recent usage includes hardware equipment like conveyor belts, robotic arms, and automated guided vehicles (AGVs), which move and handle goods in the warehouse environment [7]. Internet of Things (IoT) devices transmit data constantly on inventory, equipment, and conditions, enabling operators to monitor and control operations in real-time [8]. The software is the backbone of management, responsible for activities such as store products at predetermined locations, order-picking process and packing process for maximum efficiency [9]. Automated warehouses boost productivity through task automation with the above advanced hardware and software to meet the rising demand of the logistic operations for online retail. Despite important steps are increasingly being taken for automation, energy consumption remains a major issue in automated warehouses. The European Commission supports this concern through proposing Industry 5.0, in which resilient and sustainability are important focuses [10]. While Industry 5.0 also focuses on human-related issues, this paper only examines the operational efficiency and energy sustainability of fully automated warehouses.

Sustainability and resilience in fully automated warehouses are challenging when the trade-off is energy efficiency versus operational productivity [11,12]. On one side, reducing energy consumption or the carbon footprint of operations is the aim of sustainability initiatives [13]. Resilience initiatives need warehouses to ensure that their functioning can handle peak or unforeseen demand. To accomplish this, equipment is often run beyond design capacity, and backup systems are maintained, which boosts energy consumption [14]. For instance, increasing operational efficiency to respond to the rise of e-commerce usually means adding automated machines and extending working hours, both increasing energy consumption. In addition, an aggressive energy-saving strategy, such as reducing equipment capacities and running times, will weaken warehouses' responses to uncertainties. The two conflicting objectives show a trade-off between sustainability and resilience in managing automated warehouses.

Past research has optimized sustainability and resilience in automated warehouses while considering single processes. Riazi et al. [15], for instance, focused on reducing energy with increased resilience in AGV order picking. Although useful, these studies have a narrow focus that misses how different warehouse operations interact and are dependent on each other. To overcome these limitations, simulation plays a key role in automated warehouse management by creating a virtual environment to model, analyze, and optimize the complex interactions of automated warehouse operations. A digital twin (DT) shows good potential for this complex simulation, offering a virtual duplicate of an automated warehouse that gives a highly accurate representation [16]. A DT can continuously reflect the real status of the warehouse through real-time data collected via sensors [17]. Stakeholders of DTs can perform scenario testing, predictive maintenance, real-time optimization, and simulation of processes for better decision-making to enhance both sustainability and resilience. Therefore, a Digital Twin for Joint Sustainability and Resilience Optimization (DT-JSRO) model has been proposed in this study that optimizes sustainability and resilience. The DT-JSRO model creates a digital twin of the warehouse for dynamic simulation based on real-time information. The proposed model helps to evaluate trade-offs between reducing environmental impacts and improving the capacity of the system. The DT-JSRO model uses "what-if" scenarios to help stakeholders optimize warehouse operations for level-of-service, cost, or flexibility. The proposed model will make logistics systems more sustainable and resilient in nature, ultimately contributing to the transition to Industry 5.0.

The novelty of this study lies in its shift from traditional, isolated optimization approaches to a coupled framework that concurrently evaluates the trade-off between sustainability and resilience. While current digital twin warehouse solutions predominantly focus on minimizing processing time or optimizing individual tasks (e.g., routing) under idealized conditions, the proposed DT-JSRO framework introduces a holistic digital representation that captures the interdependencies of core logistics processes under realistic industrial power constraints. This enables a quantitative mechanism to dynamically balance the energy penalty of maintaining active infrastructure against the operational robustness required to handle demand fluctuations—a crucial alignment with the goals of Industry 5.0 that existing models lack.

Building upon this novel foundation, the main contributions of this work are summarized as follows:

- A holistic DT framework for coupled operations: Unlike existing models that isolate single warehouse processes, the DT-JSRO integrates the core, highly interdependent operations (replenishment, picking, and packing) to prevent bottleneck-shifting and optimize system-wide performance.
- Joint optimization of conflicting objectives: A quantitative mechanism is introduced to evaluate the trade-off between sustainability (energy minimization) and resilience (throughput maximization under dynamic constraints).
- Realistic energy billing modeling: An hourly ceiling billing mechanism is incorporated to account for both mobile resource consumption and fixed warehouse environmental loads. This provides a more accurate reflection of actual industrial operational costs than traditional 24/7 fixed-load assumptions.

The rest of the paper is arranged accordingly: Related work in automated e-fulfilment centers, how Industry 4.0 evolves to Industry 5.0, and digital twins are reviewed in Section 2. The design of the DT-JSRO model is detailed in Section 3, while a simulation experiment is presented in Section 4. Section 5 discusses the results and comparison, from which Section 6 provides a detailed summary and the final conclusions.

2. Literature Review

2.1. Automated Warehouses in E-Commerce Logistics

As e-commerce is growing, there is a rise in e-fulfilment centers. These centers encounter critical challenges in the handling of e-orders that require shorter lead times, responsiveness in real-time, and order-processing in large volumes with greater variety and flexible processes [18]. Traditional manual warehousing systems are not able to cope with the scale and speed demanded by online retailers. These retailers face customers who are buying by impulse. Also, there are constantly changing order details. Most often, they are required to deal with a huge volume of return flows [19]. Investing in automated warehouse solutions has become important to meet these changing requirements and remove operational bottlenecks. Being able to automate processes enables warehouses to scale effectively to cope with the unstable electronic retailing orders. Robotic process automation and optimizing space consumption reduce repetitive work at the fulfilment center, and as such, these centers can manage increasing order volumes without a corresponding increase in workforce or space.

Automated warehouses leverage AGVs, Automated Storage and Retrieval systems (AS/RS), robotic arms, and conveyor belts to transform traditional warehousing into intelligent systems capable of enhanced functionality and autonomy [20]. Azadeh et al. [21] illustrates the typical operations of automated warehouses, including good receiving, replenishing, picking, packing, and preparing the goods for the outbound process. In such a process, suppliers unload preannounced pallets, each with a single stock-keeping unit (SKU), onto a conveyor. These pallets are then stored in the AS/RS, which retrieves and breaks down the pallets if necessary. Cases are put on trays for convenience and stored in a smaller AS/RS for quick access. When a store puts an order, the cases are picked, sequenced and packed into pallets or roll cages for easy shelving. Newly completed roll cages are temporarily stored in a consolidation buffer until they can be loaded in delivery order. During the process, AGVs play a crucial role for order picking, which is the most labor-intensive, error-prone, and costly operation in modern warehouses [22]. AGVs remove the need for human pickers to travel back and forth during order picking, improving efficiency and accuracy [23]. The purpose of the automated warehouse is to achieve savings on labor costs and floor space, increased reliability and a lower error rate compared to traditional warehouses [24]. Also, these automated systems can work 24/7 since they do not need breaks like human workers do [25].

2.2. Industry 5.0 for Sustainable and Resilient Automated Warehouses

Automated warehouses are one of the core Industry 4.0 applications that are smart and effective due to advanced technologies. The main objective of industry 4.0 focuses primarily on automation and digital integration to enhance efficiency and productivity. Industry 5.0 is an extension of Industry 4.0, focusing on the human-centric, sustainability, and resilience [26]. While the machines drive Industry 4.0, a key advantage of Industry 5.0 is that it optimally uses the strengths of machines and humans. The intelligent automation of humans' creativity, intuition, and decision-making is key to creating flexible warehouse systems that can respond to the changing demands of modern supply chains.

Enhanced control systems and improved predictive maintenance in automated warehouses in Industry 5.0 will cut down energy consumption. As these technologies help save energy and reduce equipment downtime, they result in an increase in asset lifespan, while also generating less waste [27]. When demand is low, AS/RS can run at a lower capacity. Machine breakdowns are prevented when predictive maintenance is regularly conducted. Thus, no downtime or waste of resources will occur. Warehouse sustainability techniques help in creating greener warehousing solutions that save energy.

The use of various real-time tracking, adaptive robots, and AI-based decision support systems enhances system resilience to continue the operations under the varied demands and uncertain conditions in the e-commerce supply chain [28]. Robots and AGVs are adaptable to order increments and product variety, and unplanned disruption from the supply delays and labor shortages. This adaptability allows warehousing to fulfill requests precisely and deliver products on time even when they encounter uncertainties.

In contrast to traditional automated warehouses where humans play a lesser role, they need to be the center of warehouse operations as per the concept of industry 5.0. Human-centric collaboration of technologies and humans is an integration of human creativity, problem-solving, and control with automation systems that enables faster and more flexible responses to complex problems [29]. Industry 5.0 is changing the automated warehouse from just another efficient machine into an intelligent, sustainable, and resilient ecosystem.

As a result of the increasingly complicated logistics processes of e-commerce that warehouses are facing, Industry 5.0 is making it feasible to use advanced automation together with human collaboration, intelligent energy management, and flexible technologies.

2.3. Digital Twin for Transitioning to Industry 5.0

Even though the importance of Industry 5.0 generated wide-ranging discussions and an increasing interest among different stakeholders, it remains an emerging paradigm that is still developing and not yet fully achieved in practice. Several scholars are making an effort to ease the transition to Industry 5.0 with the help of Enterprise Resource Planning (ERP), Warehouse Management Systems (WMS), and IoT to optimize warehouse operations et [30,31]. Advanced smart warehouse ecosystems can collect, analyze and use real-time data for extensive decision making. Using IoT devices in the warehouse would create continuous monitoring of environmental, inventory and mechanical data, with the possibility of dynamic management and predictive maintenance [32]. WMS helps move and manage materials between processes such as order processing and helps control inventory within a facility [33]. ERP connects all warehouse operations with the broader supply chain and the organization.

When these technologies work together, it ensures that data and information can flow smoothly through every level of the organization. The use of digital twin (DT) technology could significantly optimize sustainability and resilience towards transition of Industry 5.0. A DT is a virtual representation that continuously updates and integrates real-time data from physical objects, systems, or processes [34,35]. As illustrated in Figure 1, the lifecycle of the DT is a continuous loop between the real-world and its virtual representation. The first step is to capture and store data from the physical to digital warehouse. After that, this data is analyzed for simulation. The insights and results are then transferred back to the real system for operational adjustment. The model continually tracks, simulates and analyzes operations for inefficiencies. It may be used to predict disruptions and test optimization strategies without affecting real-world operations [36].

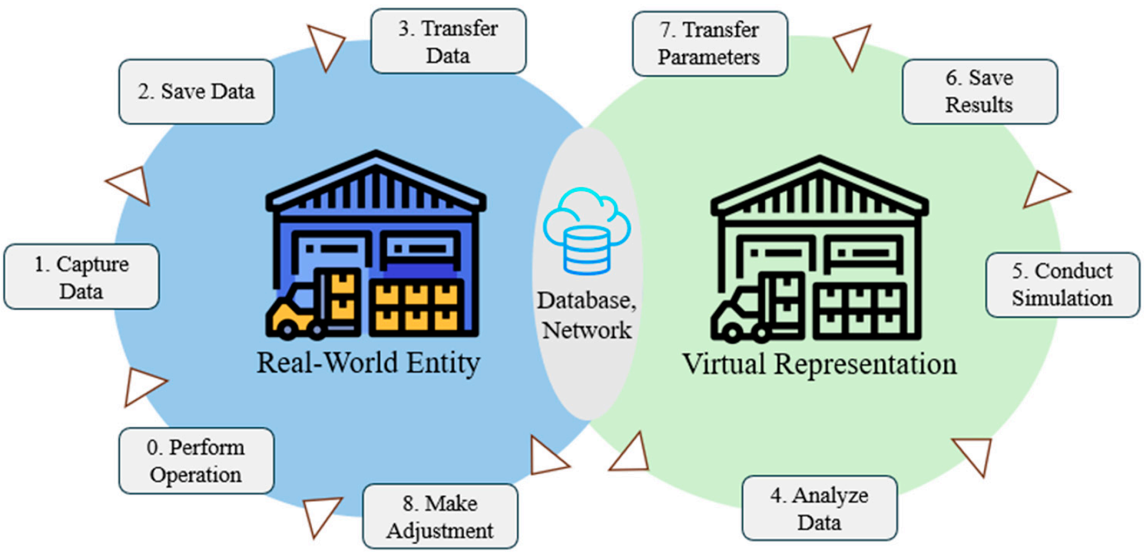

Figure 1. Digital twins for an automated warehouse.

Use of DTs is growing rapidly in the logistics application. Reference [37] created a DT-based model which is used for dynamic scheduling problems for goods picking with AGVs in factory logistics. The simulations can be used to determine the ideal number and operating speeds of AGVs in different operational environments. Reference [38] developed a virtual plant factory to enhance AGV scheduling in order picking, with the aim of optimization on energy consumption and the makespan. Reference [39] applied a DT in picking activities, with the purpose of reducing the time of use of the forklift and the repositioning of the bags. This optimization positively impacts the societal and environmental landscapes through increased resilience and reduced energy consumption.

2.4. The Need for a Holistic Digital Twin Approach in Automated Warehouses

DT has shown some promising potential to optimize a warehouse's various operations and functions. However, specific research studying DT applications in an automated warehouse with a twofold sustainability and resilience focus is lacking. Also, the majority of current studies focus on isolated processes, such as order picking, and ignore the interrelated nature of logistics processes. Recent studies show that scholars are starting to realize that warehouse operations can be viewed as integrated processes as a whole [40]. Poor assignments to storage locations can lead to extended travel time for pickers, thus reducing their efficiency in order picking [41].

As the concept is gaining popularity, there is a greater focus on merging two or more operations into the warehouse for joint optimization. Reference [42] developed a joint order picking and delivery optimization model using mixed-integer programming by interpreting the joint problem as a synchronization one. They concentrate on the trade-off between picking velocity and picking station utilization, which is a major determinant of operational efficiency and sustainability. Reference [43] employed a DT to improve the joint processes of replenishment and order fulfilment at distribution hubs. The growing potential of DTs in automated warehouse management is highlighted in this work through the integration of the most critical and interconnected warehouse processes (replenishment, picking, and packing) in an integrated system. Moreover, [44] states that it is possible to save energy as well as reduce delay by optimizing AGV movement through a DT with deep reinforcement learning. The benefits of interconnected operations are shown by current coordination efforts.

2.5. Research Gap and Summary

Despite growing interest in the use of DTs for automated warehouse optimization, most of existing research investigates isolated warehouse operations rather than investigating interconnection of logistics operations. Furthermore, current solutions frequently assume idealized energy consumption or focus entirely on processing time, failing to capture the practical cost of maintaining active but idle equipment.

Also, few existing studies have focused on sustainability or resilience but not both. With introduction of new technology demands and growth of e-commerce, warehouse operations are likely to become complex. Therefore, there is a critical need for a system that dynamically balances the energy penalty of running idle infrastructure against the operational resilience required to absorb sudden order surges. To achieve holistic models that enhance sustainability and resilience, the interactions of the key processes which include replenishment, picking and packing have to be considered under power constraints.

In order to fill this gap, this study proposes a DT-JSRO model. The model uses operational data to create a virtual twin of the automated warehouse. Using this model, various scenario-based analyses were performed to judge the trade-offs between operational robustness and environmental performance. This framework enables stakeholders to identify bottlenecks and monitor energy consumption across the interlinked operations without hindering activity performance. The simultaneous enhancement of sustainability and resilience through the DT-JSRO is highly valuable for automated warehouse management, towards the development of smart, adaptive, and sustainable logistics systems in line with Industry 5.0 principles.

3. Methodology

3.1. Introduction of DT-JSRO

This research proposes a DT-JSRO model to tackle the resilience and sustainability challenges in automated e-fulfilment centers. The model architecture enables a focused yet integrated digital representation of the core order-fulfilment processes in automated warehouses for supporting decision-making in the key processes. The DT-JSRO model allows simulating various scenarios and evaluating performance by representing the core order-fulfilment processes (replenishment, picking, and packing). This will enable the formulation of optimal resource allocation strategies with enhanced operational performance and reduced energy consumption. The architecture of the DT-JSRO model is shown in Figures 2 and 3, illustrating the process flow of the DT-JSRO architecture in automated e-fulfilment centers. To distinguish the DT-JSRO framework from existing digital twin and warehouse optimization approaches, the focus is fundamentally shifted from isolated task management to a joint optimization paradigm. While conventional models often address order picking or equipment routing independently to minimize processing time, the DT-JSRO integrates the highly interdependent operations of replenishment, picking, and packing into a single virtual ecosystem. Furthermore, it incorporates realistic industrial power constraints, such as an hourly ceiling billing mechanism that accounts for fixed warehouse environmental loads. This enables the system to dynamically balance the energy penalty of running idle infrastructure against the operational resilience required to absorb sudden order surges, allowing management to evaluate coupled sustainability and resilience trade-offs rather than optimizing a single metric in isolation.

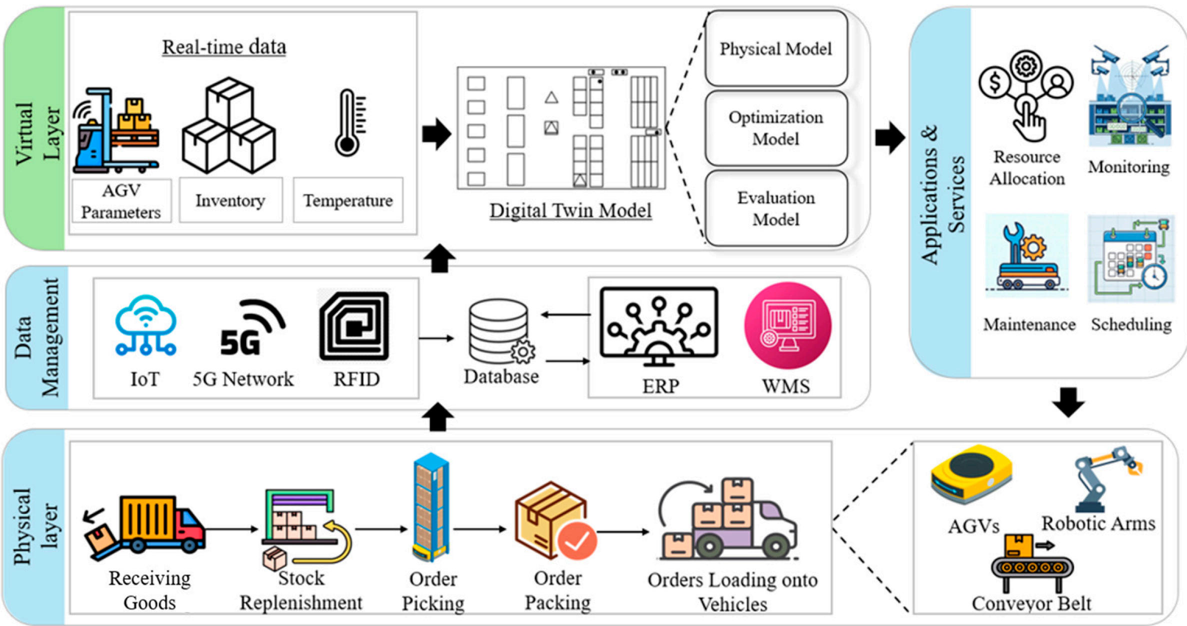

Figure 2. DT-JSRO architecture for automated warehouses.

Physical layer warehouse operations consist of operations that are related to the core of a warehouse, such as receiving, replenishment, picking, packing, and loading. Such operations are done with equipment such as AGVs, robotic arms, and conveyors. However, the current implementation focuses on the three core flow processes of AGVs (replenishment, picking, and packing) because they dominate resource utilization and often exceed

50% variable electricity consumption in an automated warehouse [45], the same as in most e-fulfilment centers. Other activities, such as receiving goods and outbound loading, are intentionally excluded from the model scope because their operational nature makes them less suitable for this joint optimization framework. These excluded processes are often handled by fixed conveyors or dock equipment that draw near-constant power load, meaning their scheduling has very limited interaction with real-time picking dynamics and contributes relatively little to the variable energy consumption of the facility. By narrowing the boundaries to the three tightly coupled internal processes, the model maintains a high degree of mathematical tractability and interpretability while still capturing the vast majority of adaptable energy savings and operational bottlenecks. These activities will generate real-time operation data, which refers to the continuous stream of sensor and system data collected from the physical warehouse and transmitted via IoT/5G/RFID to the central database (ERP/WMS). This includes but is not limited to:

- Current position, speed, battery level, and state of each AGV;
- Environmental parameters (temperature, humidity—optional for future energy models);
- Inventory levels at each storage location and picking face;
- Order arrival times, order lines, and due dates;
- Queue lengths at packing stations and charging stations;
- Current number of active mobile resources and their utilization.

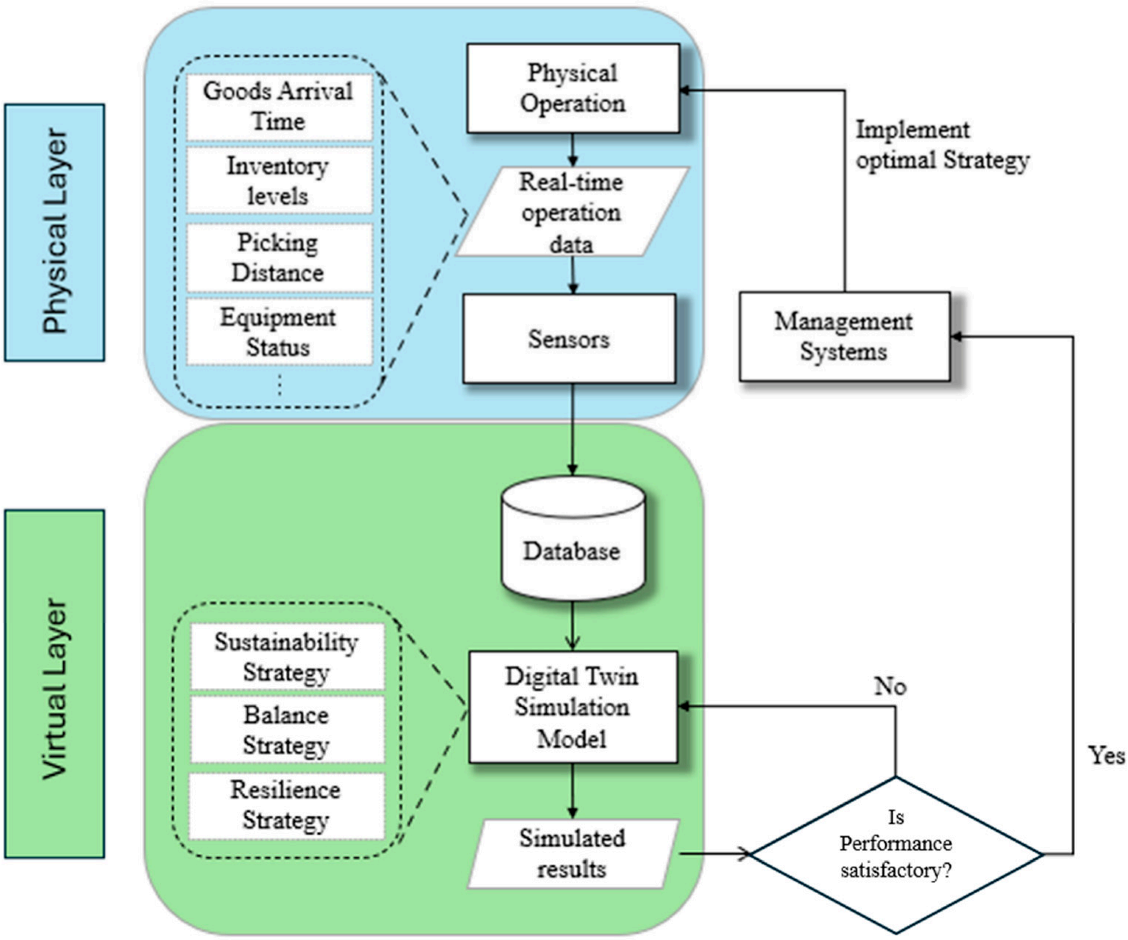

Figure 3. Process flow of DT-JSRO.

In each simulation cycle of the digital twin (typically every 10–60 s in a real deployment), the virtual layer ingests this real-time snapshot together with forecasted near-term order volume (e.g., next 1–2 h). The reason for choosing this updating frequency is that it balances computational efficiency and operational responsiveness. Tasks like AGV transit, order picking, and replenishment typically cost several minutes to complete. Updating the digital twin at a sub-second frequency will not be effective as it will introduce severe data congestion and computing overhead, while the physical state will not have changed significantly. On the other hand, an update interval exceeding a few minutes would result in the virtual model being left behind due to sudden disruptions, such as an immediate queue build-up at the packing stations. Therefore, a 10 to 60 s interval is determined to be the optimal window to capture critical state shifts while maintaining a lightweight, real-time feedback loop.

The virtual layer uses these data to build a DT model with a physical, optimization, and evaluation component that simulates warehouse operations with different strategies. To describe this feedback loop in a more systematic manner, the DT-JSRO workflow operates through a sequential, five-step process. First, during data acquisition, the physical layer captures real-time operational data (e.g., AGV parameters and inventory levels) via IoT sensors and transmits it to the central database. Second, during virtual initialization, the virtual layer ingests this real-time snapshot to populate the digital twin components. Third, the strategy simulation executes various "what-if" resource allocation scenarios based on selected operational priorities, such as balancing sustainability and resilience. Fourth, the performance evaluation phase analyzes the simulation outputs to determine whether the projected performance meets the defined objective function thresholds. Finally, during execution and feedback, the optimal strategy is transmitted to the management systems (ERP/WMS) for physical implementation if the performance is satisfactory; if not, the virtual model iterates with adjusted parameters. This continuous loop ensures operations remain focused on the defined goals.

3.2. Process Flow of the Digital Twin

This study focuses exclusively on the core operations of replenishment, picking, and packing. In order to separate and analyze interactions and performance in key stages, other processes such as receiving goods and loading are not included. Figure 4 illustrates the detailed scheduling procedure of AGVs within virtual space.

Upon receipt of a new order, the system first checks inventory levels to determine whether stock replenishment is necessary. If replenishment is required, the process enters the stock replenishment branch, where the availability of AGVs is evaluated. If no AGV is available, the system waits until one becomes free. Once an AGV is assigned, it executes replenishment by moving items from storage or receiving areas to replenish stock in the designated racks. This replenishment continues until completion, at which the inventory data is updated accordingly.

If no replenishment is needed, the process advances to the order picking branch. Similar to replenishment, the system assesses AGV availability. When an AGV is assigned to pick orders, it retrieves order items and moves them to a packing station. This repeats until completion, triggering updates to the picking job.

After either a replenishment or picking operation, the system verifies whether the AGV satisfies the charging conditions. If so, the AGV drives to a charging station and stays there until charged. Afterwards, the AGV resumes its duties. The scheduling process ensures efficient allocation, minimal waiting time and utilization of throughput in these warehouse activities.

Although a fully end-to-end warehouse digital twin would in theory include receiving goods, put-away, consolidation, and outbound loading in physical layer, the present study deliberately concentrates on the three-core order-fulfilment processes, which are replenishment, order picking, and packing, for the following reasons:

- These processes dominate variable resource utilization and energy consumption in modern automated e-fulfilment centers [14]. Mobile transport devices such as AGVs spend most of their operating time and battery capacity on replenishment tasks, order picking transport, and movements to/from packing stations.
- They are highly interdependent: poor replenishment creates picking delays and packing bottlenecks, directly affecting both sustainability (such as unnecessary waiting/idling energy) and resilience (such as reduced throughput under demand surge conditions).
- Receiving and outbound loading are typically batch-oriented, less frequent, and more predictable; their scheduling has limited interaction with real-time picking dynamics and contributes relatively little variable energy in highly automated systems, which are often handled by fixed conveyors or dock robots with near-constant power draw.

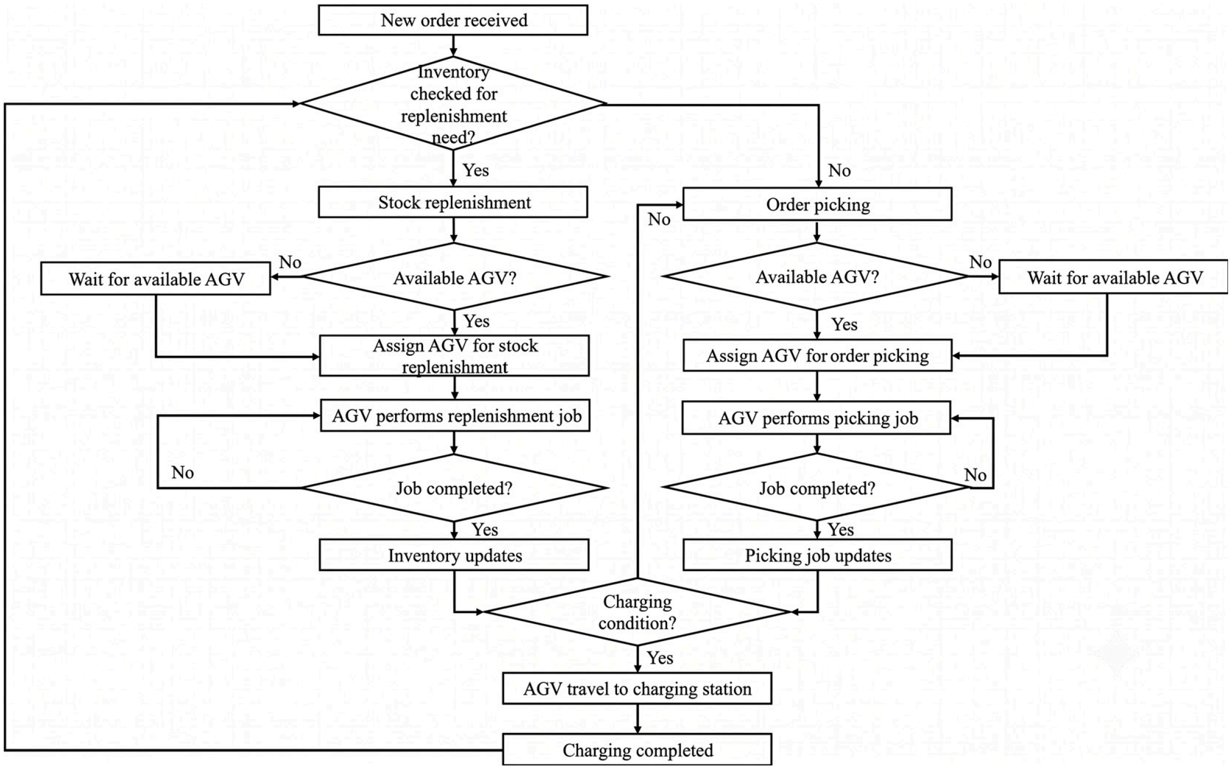

Figure 4. Scheduling procedure of AGVs in virtual space.

By focusing on these three tightly coupled processes, the DT-JSRO model captures the most significant trade-offs between sustainability and resilience while keeping the simulation tractable and the results interpretable. The architecture (Figure 2) can remains extensible: extra modules can be added in future work without changing the joint optimization objective or the digital-twin loop.

Although the current implementation and simulation experiment (Section 4) used AGVs as the primary mobile transport resource, which is assumed to be one of the most common and energy-intensive components in today's automated e-fulfilment centers, the DT-JSRO framework itself is not limited to AGV-based systems. The AGV-specific scheduling logic and energy models shown in Figures 4–6 are modular components that can be replaced or added with the corresponding models of other automation technologies such as shuttles, autonomous mobile robots (AMRs), vertical lifts, pocket sorters, robotic arms. A detailed discussion of this adaptability and concrete replacement guidelines for other systems is provided in Section 3.4.

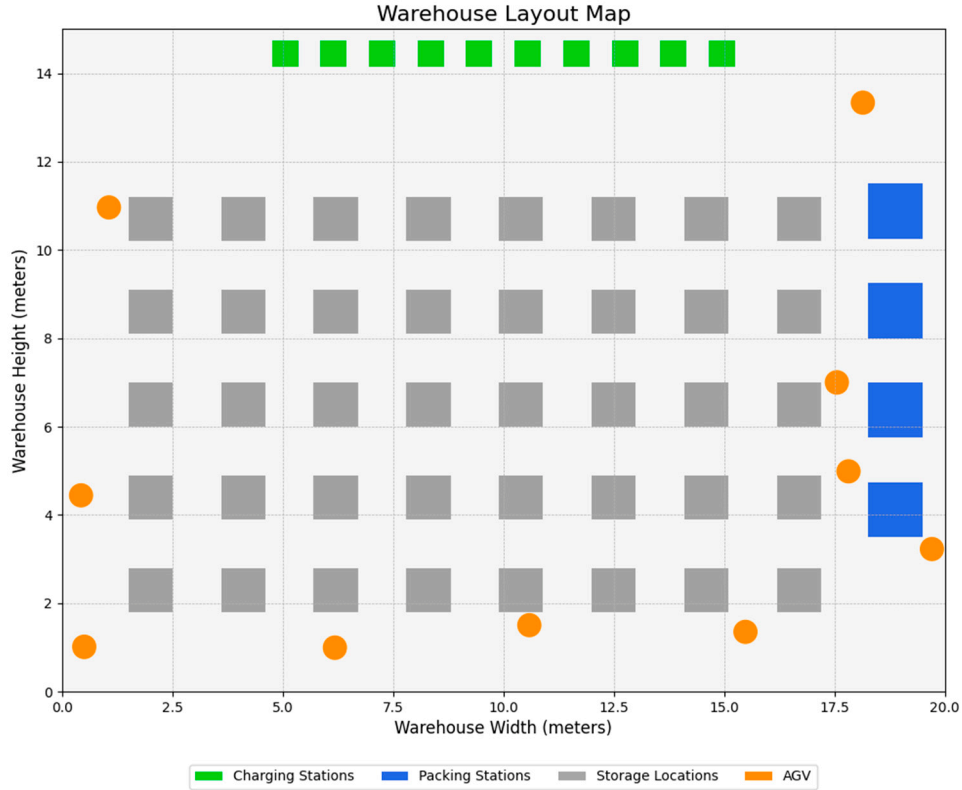

Figure 5. Warehouse layout mapping.

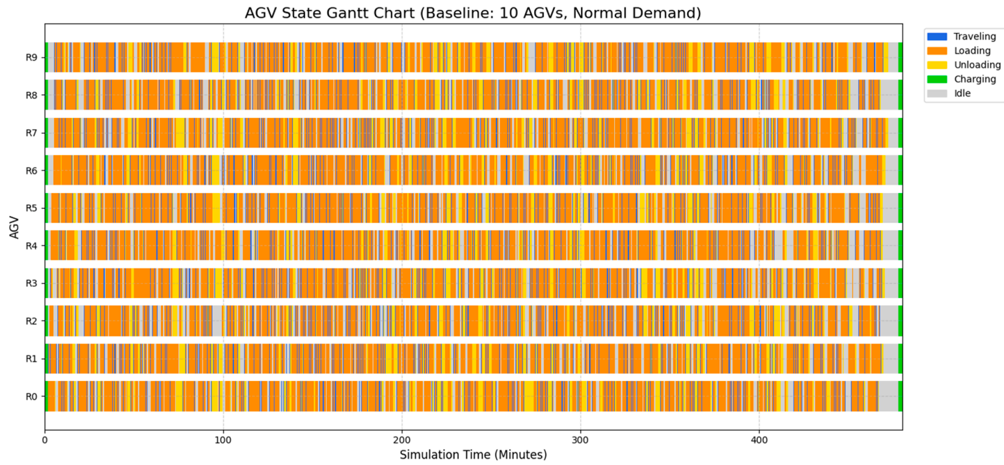

Figure 6. AGV state Gantt chart.

3.3. Simulation and Evaluation

We implemented a high-fidelity event-discrete digital twin in Python (version 3.9.7), leveraging core libraries such as scikit-learn and SimPy. The model explicitly models AGV movement, battery dynamics, charging queues, packing-station congestion, and realistic hourly ceiling energy billing for both robots and warehouse infrastructure.

3.3.1. Notation and Symbols

This section defines the key symbols and notations used throughout the study. Let k∈{1,. . .,N_{agv}} denote the index for each AGV in the fleet, where N_{agv} is the sum of AGVs operating in an automated warehouse. The indices i,j ∈ {1,. . .,N_{loc}} indicate a discrete location in the warehouse, such as a storage rack, packing station, or charging station, where N_{loc} is the total number of such locations. The term t refers to the simulation time, which may be taken as either continuous or discrete. The Δt refers to the discrete time-step interval used for updating the simulation state. The battery energy level of AGV k at time t is denoted by E_k(t) and is expressed in kilowatt-hours (kWh). This variable is updated dynamically based on AGV actions. Orders generated during the simulation are indexed by o $\in$\{1,. . .,O_{total}\}, with O_{total} being the total number of orders. The subset $O_{comp} \subseteq O_{total}$ represents all orders that have been successfully completed and delivered within the simulation timeframe. The average order cycle time L_{avg} is defined as the mean duration, measured in minutes from arrival to the completion of orders within the completed set O_{comp}.

3.3.2. Mathematical Formulation and Objective Function

This section presents the key mathematical equations underlying the DT-JSRO model and the joint optimization objective function designed to balance sustainability and resilience in warehouse operations. For each AGV k, the battery energy level E_k(t) at simulation time t updates dynamically based on its activity mode A_k(t), where

$$A_k(\mathrm{t}) \ \in \{traveling,\ idle,\ charging\} \tag{1}$$

The energy consumption or recharge over a discrete time step Δt is defined as

$$E_k(\mathrm{t} + \Delta t) = E_k(\mathrm{t}) - \Delta E_k \tag{2}$$

where

$$\Delta E_k(\mathrm{t}) = \begin{cases} P_{move}\ .\ \Delta t,\ if\ A_k(\mathrm{t}) = traveling \\ P_{idle}\ .\ \Delta t,\ if\ A_k(\mathrm{t}) = idle \\ -P_{charge}\ .\ \Delta t,\ if\ A_k(\mathrm{t}) = charging \end{cases} \tag{3}$$

Here, P_{move} , P_{idle}, P_{charge} and $P_{\mathrm{warehouse}}$ represent the power rates for traveling, idling, charging and warehouse infrastructure respectively. Two primary KPIs, derived from simulation outputs, are used to evaluate system performance. The first one is the sum of all energy consumed; the second one represents the total orders completed.

$$\begin{gathered} E_{total} = \left(\sum_{k=1}^{N_{agv}} E_k + E_{\mathrm{awake}}\right) \\ + P_{\mathrm{warehouse}} \cdot L_{avg} \cdot O_{total} \end{gathered} \tag{4}$$

The objective function aims to minimize a combined cost reflecting both sustainability and resilience aspects of warehouse operations. The function is designed to be flexible, allowing users to prioritize these goals by adjusting two key weighting factors: W_s for sustainability and W_r for resilience. In this study, both the weightings are set to be the same. Specifically, it balances the total energy consumed by the AGV fleet with penalties related to order fulfillment performance, including both unfulfilled orders and the average time taken to complete orders L_{avg}.

$$\text{Min Cost} = W_s \cdot normalized\_energy + W_r \cdot normalized\_makespan \tag{5}$$

The DT-JSRO explicitly targets the joint optimization of operational energy (sustainability) and order completion time (resilience) through the weighted objective function. This optimization is governed by three primary constraints: (1) AGV battery levels must remain within hardware limits, forcing immediate charging when depleted; (2) all generated orders must be fully processed before the simulation terminates; and (3) tasks are strictly assigned to idle AGVs, with pending tasks queued. Finally, system performance is evaluated using two key metrics: total energy consumption (aggregating variable fleet usage and fixed infrastructure loads) and the makespan (total hours required to process all orders).

Although real automated warehouses may include additional processes such as sorting, staging, consolidation, or value-added services in physical layer, these are typically assumed to be performed either by fixed or semi-fixed equipment such as robotic arms. A notable source mentioned that conveying equipment (including AGVs and other mobile devices) can consume up to 50% of facility energy usage in automated warehouses [14] which contain same assumption in the simulation experiment. However, when a specific warehouse has energy-intensive fixed sorters or robotic cells that dominate consumption, their power draw can be added as an additional term in Equation (1) or treated as a throughput-dependent background load; as a result the overall DT-JSRO architecture and joint objective function remain unchanged.

3.3.3. Hourly Ceiling Energy Billing with Shared Warehouse Environment Load

A major limitation of existing warehouse digital twin studies is the unrealistic modeling of fixed energy consumption and real-world electricity billing. While variable energy from movement and lifting is usually captured accurately, fixed loads such as robot onboard electronics (approximately 80 W per AGV for LiDAR, computers, and sensors) and shared warehouse infrastructure (lighting, HVAC, WMS, Wi-Fi—typically 3–15 kW) are either ignored or assumed to run 24/7. In actual industrial contracts, however, these loads are subject to hourly ceiling billing: any activity lasting even one minute within a clock hour triggers a full-hour charge.

A shared warehouse fixed load (set to 5 kW in the simulation experiment) is activated only when at least one robot is active and is similarly billed using hourly ceiling logic via a dedicated minute-by-minute monitoring process. This realistic billing model dramatically alters the sustainability–resilience trade-off: low fleet sizes incur high warehouse fixed costs due to prolonged operating hours, whereas excessive fleet sizes trigger a steep rise in robot electronics (such as LiDAR and sensors) costs even when robots are idle-but-awake.

3.4. Generalization and Adaptability of the DT-JSRO Framework to Different Automation Technologies

Although the simulation experiment in Section 4 focuses on an AGV-based warehouse, the DT-JSRO framework (Figure 2) is basically designed to be technology-agnostic at the architectural level. The physical layer collects real-time data streams (position, speed, energy state, task status, queue lengths, etc.) from whatever automated equipment is deployed in any warehouse. The virtual layer consists of three replaceable modules: Physical twin modules can mirror real resources from any type of warehouse with specific functionality, for example, AGVs in floor transport warehouses, vertical sequencers, and robotic arms in robotic piece-picking cell warehouses, while optimization modules can apply different dispatching rules, routing logic, and energy models specific to the dominant equipment. The evaluation model(s) can be modified according to users' requirements.

Only two elements are technology-specific and must be adapted when moving to a different automation solution: the energy-consumption and motion models, for instance, replacing AGV battery dynamics with shuttle/lift power profiles. Meanwhile specific low-level dispatching and sequencing heuristics are applied according to the specific warehouse environment (e.g., replacing AGV task-to-vehicle assignment with shuttle port allocation or pocket-sorter induction sequencing).

4. Simulation Experiment

This section describes a simulation experiment to study the performance proposed DT-JSRO model in an automated warehouse environment. The simulation aims to test the model's capability to optimize sustainability and resilience through integrated process synchronization and resource allocation.

4.1. Environment

The proposed DT-JSRO framework was validated through a simulation-based digital twin experiment that replicated the key operational processes of an automated warehouse. The validation focused on testing the framework with different operational scenarios and sensitivity settings, including variations in the number of AGVs, charging stations, packing stations, and order volume. The effectiveness of the framework was assessed using key performance indicators such as order completion time, total energy consumption, and execution time. The results showed that the framework can capture system behavior realistically, identify bottlenecks, and support better resource allocation decisions by balancing sustainability and resilience objectives.

The evaluation of the proposed DT-JSRO framework relies on a simulated environment adapted from the established benchmarking framework of Chow et al. (2026) [46]. A simulation-based setup was selected because it provides a safe, flexible, and risk-free sandbox to test complex joint optimization algorithms and extreme disruption scenarios without endangering physical warehouse assets or interrupting live workflows. To better reflect the intense density and operational bottlenecks of modern e-fulfillment hubs, the baseline parameters from [46] were revised to incorporate higher structural complexity, including an expanded AGV fleet and increased downstream packing station capacity.

A simulation was conducted which the length and width of warehouse were given as 20 m and 15 m respectively. In the warehouse, there are 40 racks (1 m $\times$ 1 m) for storage. AGVs charge at 10 charging stations, with 0.6 $\times$ 0.6 each. Four packing stations are provided with a dimension of 1.25 m $\times$ 1.25 m. The packing stations are equipped with conveyors and robotic arms for packing operations. The fleet comprises 10 AGVs, with a radius of 0.275 m, designed to transport goods. The energy consumption of AGVs varies depending on their activity, with a higher drainage rate of 0.45 kW while traveling compared to a lower rate of 0.08 kW when idle. Additionally, the recharge process at charging stations replenishes the AGV battery at a constant rate of 1.5 kW. The modeling parameters are summarized in Table 1. Figure 5 visualizes the virtual warehouse layout in this simulation.

Table 1. Parameters of the layout and operation.

Parameter	Description	Value
N_{agv}	Number of Automated Guided Vehicles (AGVs)	10
N_{pack}	Number of packing stations	4
N_{charge}	Number of charging stations	10
N_{store}	Number of inventory storage locations	40
T_{sim}	Total duration of the operational shift in hours	8
O_{total}	Total number of orders generated in a shift	1000
V_{agv}	The travel speed of an AGV in meters per second	1.7 m/s
P_{idle}	The power consumed by an AGV while idle	0.08 kWh
P_{move}	The power consumed by an AGV while moving in kilowatts (kW)	0.45 kWh
C_{bat}	The battery capacity of an AGV in kilowatt-hours (kWh)	2.0 kWh
P_{charge}	The power supplied by a charging station in kilowatts (kW)	1.5 kWh
A_{wh}	The physical dimensions (width and height) of the warehouse in meters	(20, 15)
S	The set of unique inventory types (SKUs)	6 types
$P_{warehouse}$	The power consumed by warehouse infrastructure	5 kWh
E_{awake}	The energy per AGV when awake	0.5 kW

4.2. Model Assumptions and Scope

The focus on the main process interactions is strengthened by excluding peripheral activities such as goods receipt and outbound logistics. It assumes that AGVs operate autonomously according to an established schedule and routing rules. Further, their travel times, energy consumption, and charging behaviors are pre-determined. The levels of inventory and the arrival of orders are modeled from history using a first-come, first-served order fulfillment unless specified otherwise. The environment is supposed to be stable and safe. There is no accident or collision. There are no other uncertainties such as errors or system malfunctions. Job selection, AGV assignment, and charging decisions implemented on the DT rely on rule-based heuristics. Moreover, the objective of optimization is to minimize energy use and penalties for unfulfilled orders with managerial balance between priorities. It is assumed the penalty for not fulfilling an order is very high, suggesting that providing a consistent service is crucial for these businesses, so that customer satisfaction remains high, even at the cost of spending slightly more energy.

The DT-JSRO model tracks the energy consumption of AGVs performing stock replenishment, order picking, and transporting inventory to the packing station. This allows for a detailed assessment of energy usage of AGVs because AGVs' energy demand is a major component of automated warehouse operation. Figure 6 shows the state shifts of eight AGVs during the simulation. The simulation was carried out for 480 min under normal demand conditions. The Gantt chart categorizes the AGV activities as traveling, loading, unloading, charging and idle. The most time-consuming tasks for AGVs are loading, which is a very high workload task involving picking, and replenishment. Constantly switching from loading to unloading indicates that AGVs are continuously working to move the inventory from storage locations to packing stations. Sections of travel are interspersed at regular intervals indicating movement across operating areas. Idle periods are less throughout the simulation; hence, AGVs are constantly used. The amount of time spent charging was relatively infrequent and short. This indicates effective energy management and scheduling that prevents downtime during battery charging.

5. Results and Discussion

The relationship between time for task completion and the total energy used is illustrated in Figure 7. For hourly peak-demand billing, the trade-off shows a clear trend which is greatly influenced by the fixed warehouse environmental load. Having two AGVs results in a long working time, which ultimately leads to massive total energy consumption. This is due to the billing of the constant 5 kW fixed operational energy consumption (lighting, HVAC, etc.), over a much longer period. As the number of AGVs changes from two to 10, the total energy consumption drops steeply because the addition of robots significantly reduces order completion time. Thus, the savings on fixed operational energy consumption is very large even though the robot-related charges increase moderately.

When the number of AGVs lies in the range of 10-16, the decrease rate in energy consumption slows down and reaches the minimum energy consumption around 15-18 AGVs. This represents the optimal fleet size for minimizing total energy expenditure. Beyond this point, further increases in fleet size yields negligible improvements in completion time while incrementally increasing the energy consumption due to the hourly ceiling billing mechanism (0.5 kW per AGV charged for a full hour even with minimal activity). In contrast, the warehouse environment stabilizes once the minimum order completion time is achieved. This implies that oversizing the AGV fleet beyond the optimal point results in zero performance improvements and a gradual increase in total energy consumption.

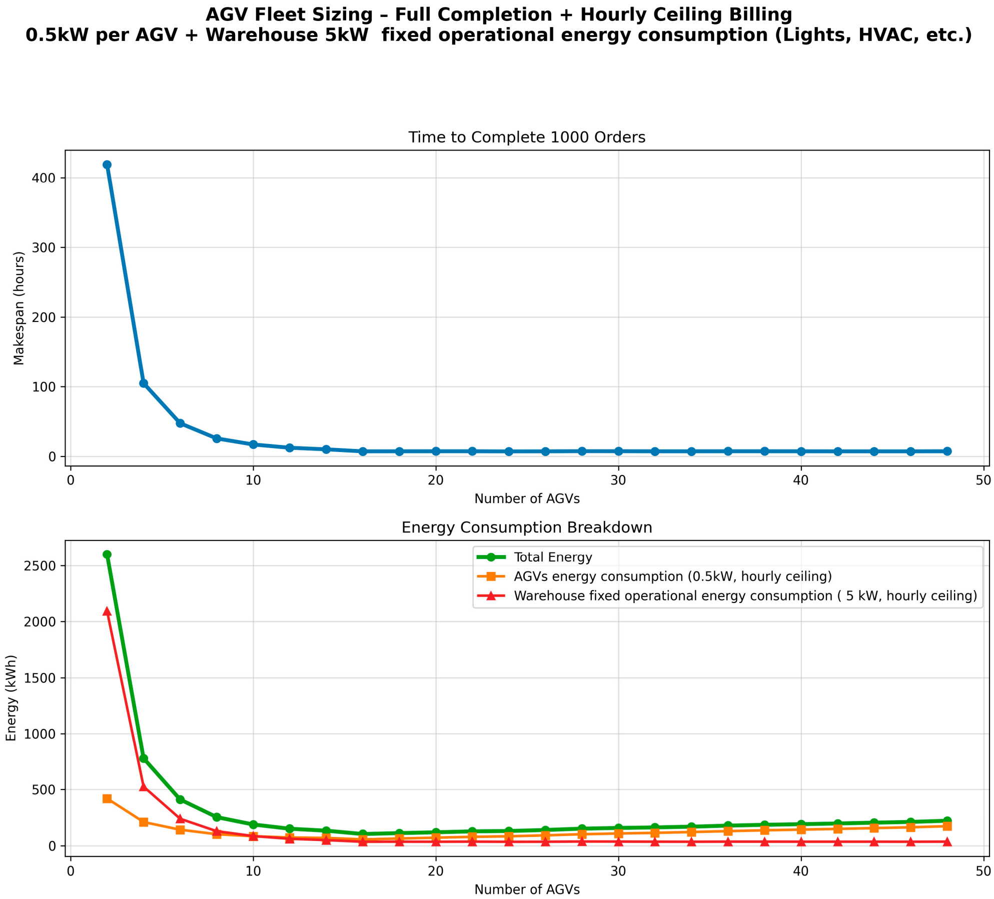

Figure 7. Simulation output of DT-JSRO.

5.1. Sensitivity Analysis

5.1.1. Impact of Packing Stations and Order Volume

To validate the robustness and stability of the proposed DT-JSRO framework under varying operational conditions, two sets of sensitivity analysis, considering packing stations and order volume, were conducted using the setting of 10 AGVs and 10 charging stations (i.e., baseline setting) to individually test the impact of order volume and packing stations. Table 2 shows all the combinations of these two sensitivity analyses.

Table 2. Combinations of two sensitivity analyses considering packing stations and order volume.

Sensitivity Analysis Focus	Number of AGVs	Number of Charging Stations	Order Volume	Number of Packing Stations	Execution Time (in Seconds)
Packing stations	10	10	1000	from 2–10	7.655
Order volume	10	10	500	10	1.315
			750		1.915
			1000		2.674
			1250		3.409
			1500		3.959

A sensitivity analysis conducted with a fixed fleet of 10 AGVs and 10 charging stations reveals that a low number of packing stations constitutes a critical system bottleneck, as illustrated in Figure 8. Due to insufficient packing stations, completion time for 1000 orders extends to approximately 37 h, indicating severe congestion at the unloading points. The limited packing capacity forces the majority of AGVs to remain idle in queues while waiting for access to a station, leading to the under-utilization of the available AGVs. As the number of packing stations increases from two to four, a significant reduction in time is observed, decreasing from around 37 h to around 18 h. This reduction in time is accompanied by a corresponding reduction in total energy consumption across AGV usage and warehouse environment usage due to the significantly shorter operational duration for hourly ceiling billing.

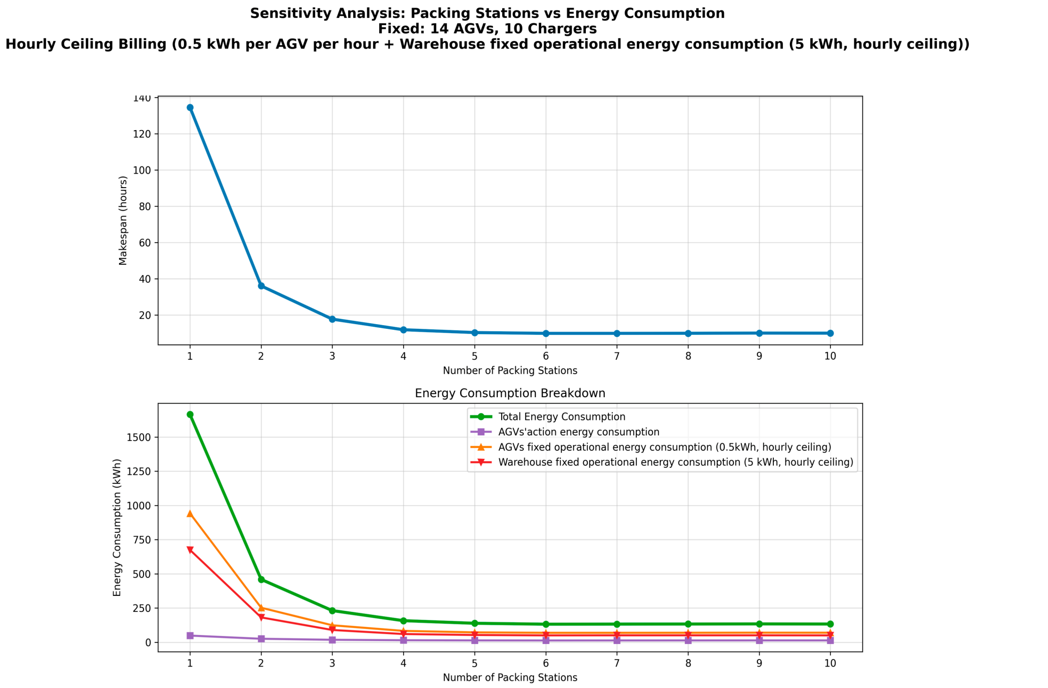

Figure 8. Sensitivity analysis on the impact of packing stations.

Adding more packing stations beyond four exhibits strong diminishing returns in both order completion time and energy consumption curves, reaching the limit at 5-6 stations. At this point, packing stations cease to constrain system throughput, and all AGVs are operating close to their maximum capacity with minimal queuing delays. These results underscore the importance of balancing the packing capacity with the AGV fleet size to avoid operational bottlenecks, which simultaneously lower performance and inflate energy consumption by extending the exposure to fixed operational energy cost.

In addition, the execution-time results indicate that the proposed DT-JSRO framework is computationally efficient and suitable for near real-time decision support. To fully justify this suitability, it is important to distinguish between empirical execution time and theoretical computational complexity. Regarding computational complexity, the framework utilizes rule-based heuristics for AGV task assignment rather than exact combinatorial optimization methods (such as Mixed-Integer Linear Programming). Because exact methods are NP-hard and suffer from exponential time scaling, they are often unsuitable for real-time digital twins. In contrast, the proposed heuristic logic operates with a low-polynomial complexity bounded roughly by $O(O_{total} \times N_{agv})$, where O_{total} represents the processed orders and N_{agv} is the active fleet size. This lean theoretical complexity prevents computational bottlenecking and translates directly to our empirical performance. Across the tested scenarios, the execution time remained very low (between 7.655 s and 1.315 s), increasing only slowly as the problem size became larger, which suggests that the model can generate useful recommendations within a practical time frame for operational use. This makes the framework appropriate for short-horizon warehouse control, where timely decisions are important for balancing sustainability and resilience.

A sensitivity analysis with a fixed setting of 10 AGVs, 10 charging stations, and 10 packing stations shows that order completion time and total energy consumption scale linearly, as shown in Figure 9. As order volume expands from 500 to 1500 orders, the completion time increases proportionally from approximately 8 h to nearly 24 h, reflecting the constant processing capacity of the robotic system. The linear trend shows that the warehouse is highly utilized at all workloads tested, with no significant spare capacity or queuing bottlenecks, which would distort scaling behavior. This confirms the system's robustness and stability, demonstrating that the framework scales predictably without suffering from exponential degradation or system failure during severe demand surges.

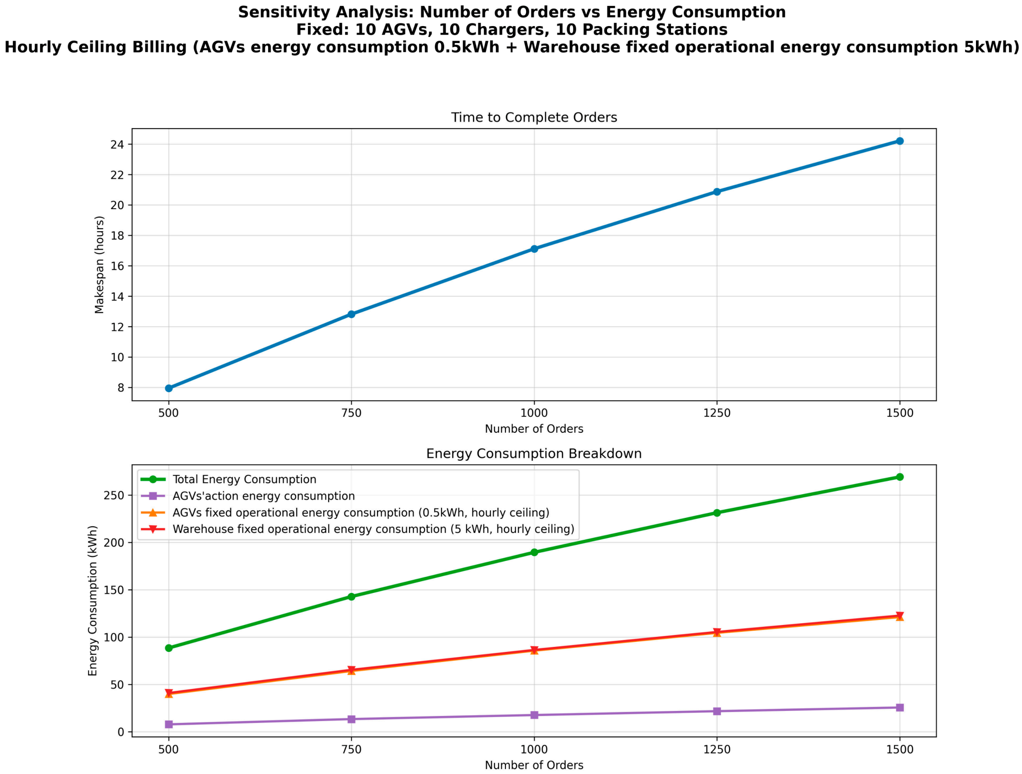

Figure 9. Sensitivity analysis on the impact of order volume.

In line with this, the total power consumption presents an almost linear trend, with the accumulation of AGV usage (movement, loading, and unloading) and fixed 5 kW operational energy consumption. The energy demand for robot electronics (0.5 kW per AGV under hourly ceiling charging conditions) is constant while the facility is active. This means that higher order volumes do not deliver economies of scale in energy intensity. Energy cost per order remains constant across the range examined. The outcome of this study implies that in a setting with fixed infrastructure and fleet size, throughput can only be increased through extending operating hours, leading to a corresponding increase in completion time and total energy consumption.

5.1.2. Performance of the DT-JSRO Model Under Varying Order and Infrastructure Conditions

In the proposed DT-JSRO framework, sustainability and resilience are quantified through a set of operational performance indicators reported in Tables 3 and 4. Sustainability is primarily measured by energy-related metrics, including AGV energy usage, warehouse infrastructure energy usage, and total energy consumption, since lower energy demand reflects reduced environmental impact and improved operational efficiency. Resilience is measured by completion time, which captures the system's ability to maintain throughput and fulfill orders under different demand and infrastructure conditions. Together, these indicators provide a practical basis for evaluating the trade-off between environmental performance and operational robustness in automated warehouse management.

Table 3. Performance of DT-JSRO with different order volumes (500–1500) and packing station quantities (2–6) using joint optimization focus.

Orders	Packing Stations	Optimal Number of AGVs	AGV Energy Usage (kWh)	Warehouse Infrastructure (kWh)	Total Energy Consumption (kWh)	Completion Time (h)
500	2	8	84.06	90	174.06	18
500	4	14	41.419	25	66.419	5
500	6	17	35.388	20	55.388	3.5
1000	2	8	179.396	195	374.396	38.5
1000	4	15	87.411	50	137.411	10
1000	6	16	67.44	35	102.44	7
1500	2	8	274.731	295	569.731	59
1500	4	15	136.479	80	216.479	15.5
1500	6	16	113.753	60	173.753	12

Table 4. Performance of DT-JSRO with 2000 order volumes using different optimization focus.

Orders	Energy Priority (W_s)	Optimal Number of AGVs	AGV Total Energy Consumption (kWh)	Warehouse Fixed Operational Energy Consumption (kWh)	Total Energy Consumption (kWh)	Completion Time (h)
2000	100%	16	140.62	71.5	213.117	14.5
2000	50%	18	147.63	70	217.63	14
2000	0%	31	233.4	67.5	300.90	13.5

From Table 3, for any given number of packing stations, the optimal number of AGVs remains consistent regardless of order volume, such that eight AGVs for two stations, 14–15 for four stations, and 16–17 for six stations, indicating that fleet requirements are primarily dictated by packing capacity rather than workload scale. Total energy consumption scales nearly linearly with the number of orders, tripling from approximately average ~100 kWh (average) at 500 orders to ~320 kWh at 1500 orders, driven by proportional increases in both AGV usage energy and warehouse environmental load due to extended operational durations.

Furthermore, the data shows a change in bottlenecked systems' composition of energy. When looking at 1500 orders and two packing stations, the energy (295 kWh) of fixed warehouse infrastructure exceeds the energy (274.73 kWh) of active AGV usages. This means poor infrastructure leads to systems with high fixed cost and low operational cost, which is a highly inefficient state.

Increasing the number of packing stations yields substantial reductions in both optimal AGV count and total energy, with the most pronounced benefits observed when moving from two to four stations. This transition achieves average energy savings of ~232 kWh across order volumes. Moreover, relieving this bottleneck produces a significant improvement in throughput velocity. As the number of packing stations triples from two to six, the effective processing rate increases fivefold from 25 orders/h (59 h overall) to 125 orders/h (12 h overall). Further increases to six stations provide diminishing returns (average savings of ~30 kWh), suggesting an optimal range of 4–6 packing stations where AGVs operate at peak efficiency with minimal queuing. The findings suggest that inadequate packing infrastructure increases energy cost through long warehouse runtime. It also leads to under-utilization of AGV fleet. On the other hand, balanced configuration (e.g., four stations with 15 AGVs offering 1000 orders) minimizes total energy to as low as 137 kWh. It offers a solution to managing warehouse costs effectively.

The AGV fleet size can be significantly optimized by increasing the weight ratio of energy priority (W_s), as illustrated in Table 4. The observation of maximum benefits essentially pertains to the shift from 0% to 50%. The average energy savings in this transition is 83 kWh. As the energy priority increases from 0% to 50%, total energy consumption decreases roughly by 28% from 300.90 kWh to 217.63 kWh. The most energy-efficient configuration is achieved with W_s = 100%. Only 16 AGVs are needed for this setting to achieve total energy consumption of at least 213.12 kWh. The maximum efficiency only increases the completion time by one hour over the makespan-only case. Thus, reasonably balanced preference settings (W_s $\geq$ 50%) can serve as a guide to achieving significant energy cost and carbon footprint reductions in large warehouses without impacting throughput.

5.2. Research Implications

5.2.1. Academic Implications

This study's novelty can be concluded in several aspects. To begin with, there is currently little research on the implementation of DTs in automated warehouses that centers on resilience and sustainability. This study closes the gap by proposing the DT-JSRO model, which offers a quantitative framework for identifying joint optimal point of sustainability and resilience. The analysis in Table 4 examines the effect of energy-priority weighting (W_s) at a fixed workload of 2000 orders. The results reveal a clear trade-off: giving full priority to energy efficiency (W_s = 100%) yields the low total energy consumption (213.12 kW) but the longest completion time (14.5 h), meanwhile ignoring energy priority (W_s = 0%) reduces completion time to 13.5 h at the cost of 41% higher energy consumption (300.90 kW). The DT-JSRO model thus provides a quantitative tool to navigate this resilience–sustainability trade-off by adjusting the priority parameter W_s and the resulting fleet size and infrastructure utilization.

Second, the findings reveal that warehouse operations are a complex process in which the fixed infrastructure of packing stations determines picking performance. According to the packing station sensitivity analysis (Figure 8), having too few packing stations (such as two stations) results in a longer completion time and a far more significant total energy consumption than more than two packing stations. The performance dramatically improves until reaching the point of sufficiency at four packing stations, at which the completion rate remains 100% and energy per order is minimized. This result challenges isolated optimization approaches by showing that process performance is also governed by its most significant bottleneck, not just the efficiency of individual components.

This study also investigates the trade-off between energy consumption and order fulfillment time in an automated warehouse by introducing an energy priority coefficient W_s $\in$ [0, 1] into the multi-objective optimization framework for AGV fleet sizing and task scheduling. For a fixed workload of 2000 orders, increasing W_s from 0 (pure makespan minimization) to 1 (pure energy minimization) reduced total energy consumption from 300.90 kW to 213.12 kW, which represents energy savings of 29.2%, while the completion time only increased from 13.5 h to 14.5 h (7.4% longer). The optimal required fleet size correspondingly decreased from 31 to 16 vehicles, demonstrating that energy-efficient operation is achieved primarily through reduced fleet size and lower congestion rather than technological measures alone. In particular, by choosing a balanced setting (W_s = 0.5), 95% of the maximum energy saving can be achieved while only suffering a time penalty that is half of the maximum. This indicates that moderate prioritization of energy can give near-optimal results on the Pareto front for most common warehouse settings. The results underline the significance of explicit energy targets in warehouse scheduling models and offer measurable evidence of the diminishing returns of aggressive throughput maximization within energy-constrained settings.

5.2.2. Managerial Implications

The DT-JSRO model is designed to improve decision-making capability of automated warehouse managers. With the help of a virtual copy of the warehouse, the users can run different "what-if" scenarios on the process change to identify bottle necks and optimizing resources planning based on their focus. For instance, the simulation shows that by using 100% energy priority (W_s) while dealing with 2000 orders a day, the resulting saving is 87.78 kW (compared to 0% energy priority). However, the completion time will be increased by one hour. This information facilitates management to make decisions when considering resource allocation related to the sustainability and resilience trade-off. Specifically, the real-time continuous data loop allows warehouse managers to dynamically reallocate AGVs and adjust charging schedules based on live sensor updates, shifting management from reactive troubleshooting to proactive bottleneck prevention. During unexpected demand surges, managers can instantly adjust the energy priority weightings within the digital twin to deploy the optimal number of idle resources, ensuring that service levels are maintained without permanently inflating fixed infrastructure costs.

Furthermore, the model also converts operational limits into financial risks. The 1500 orders are severely bottlenecked, resulting in consuming 569.73 kWh and 59 h of processing with just two packing stations. By scaling six packing stations, the total energy consumption was reduced by almost 70% to 173.75 kWh with a completion time of 12 h saving $2285 in electricity. The demonstration shows that proper packing infrastructure will be the main driver for energy and cost savings in high-volume warehouse operations. Through this approach, managers depart from theoretical discussions and rather focus on the profit and loss impact of their resource allocation and workload management. In the end, the DT-JSRO enables managers to figure out the best operational capacity of the automated warehouse and support strategic investments and policies. This ensures that the decisions as well as profit and cost are considered both resilient and sustainable.

6. Conclusions

To address the rise of e-commerce and the objective of Industry 5.0, this research proposes a digital twin framework to support the increasing demand for sustainable and resilient operations of automated e-fulfillment centers. This study proposes the DT-JSRO to support decision-making, in which a virtual representation of automated warehouses is created considering interconnected warehouse operations. As a result, warehouse managers can visualize all operational scenarios as an integrated process instead of viewing them as separate functions. This model employs a flexible objective function aimed at reaching a balance of sustainability (energy use) and resilience (performance in meeting demand in different scenarios), allowing management to prioritize as appropriate. By utilizing a DT, the overall scheduling of the AGVs will take place along with allocation of tasks and batteries. Real-time resource reallocation reduces downtime and increases throughput. The proposed model has been proved to be feasible and effective by the simulation experiment in Section 4. The DT-JSRO model results in optimal resource allocation strategies, enabling results for sustainability, resilience or joint optimization. This allows management to make better decisions and assess performance on a continual basis.

While the proposed model is beneficial in planning automated warehouse resources, it has limitations. The primary limitation lies in its heavy reliance on static, rule-based heuristics to govern task scheduling, AGV assignments, and battery charging thresholds. While these predetermined logic rules ensure system stability under baseline conditions, they lack the adaptive learning capacity required to dynamically recalibrate optimization policies when confronted with sudden, multi-variable changes in warehouse states. A secondary limitation is that the DT-JSRO model was evaluated solely within a simulated environment.

Although these simulations successfully demonstrate theoretical performance, they cannot fully capture the unstable, highly dynamic disruptions of a real-world warehouse. Consequently, applying this proposed framework to entirely different warehouse environments, such as those utilizing heterogeneous robot fleets or experiencing highly erratic and nonlinear demand patterns, may require significant manual recalibration of the underlying scheduling rules before deployment. Furthermore, the reliance on simulated validation means that practical integration challenges, such as IoT sensor latency, network packet loss, and physical hardware degradation, are not currently reflected in the performance metrics, potentially affecting the seamless transferability of the model to physical systems.

To address these boundaries, future research directions should focus on integrating advanced artificial intelligence or deep reinforcement learning into the virtual layer to enable real-time, self-learning adaptive dispatching. Furthermore, future studies must transition from theoretical simulation to practical deployment by validating the model with live operational data within physical warehouse environments, ensuring its accuracy, viability, and scalability for modern Industry 5.0 applications. Additionally, future work should explore expanding the framework to larger, more complex warehouse systems by adopting a hierarchical or decentralized optimization approach and advanced machine learning. By partitioning massive facilities into localized operational zones that run independent sub-routines, the computational complexity of large fleet sizes can be managed effectively without sacrificing real-time response capabilities.

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References

1. Statista. Retail E-Commerce Sales Worldwide from 2022 to 2028 (in Billion U.S. Dollars). 2025. Available online: https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/ (accessed on 23 June 2025).
2. Amorim, P.; DeHoratius, N.; Eng-Larsson, F.; Martins, S. Customer preferences for delivery service attributes in attended home delivery. *Manag. Sci.* **2024**, *70*, 7559–7578. [CrossRef]
3. Tabaku, E.; Duçi, E.; Lazaj, A. From Physical Stores to Virtual Marketplaces: The Evolution of Shopping. *Interdiscip. J. Res. Dev.* **2024**, *11*, 175. [CrossRef]
4. Leung, K.H.; Choy, K.L.; Siu, P.K.; Ho, G.T.; Lam, H.Y.; Lee, C.K. A B2C e-commerce intelligent system for re-engineering the e-order fulfilment process. *Expert Syst. Appl.* **2018**, *91*, 386–401. [CrossRef]
5. Li, Y.; Zhang, R.; Jiang, D. Order-picking efficiency in e-commerce warehouses: A literature review. *J. Theor. Appl. Electron. Commer. Res.* **2022**, *17*, 1812–1830. [CrossRef]

6. Odeyinka, O.F.; Omoegun, O.G. Warehouse Operations: An Examination of Traditional and Automated Approaches in Supply Chain Management. In *Operations Management-Recent Advances and New Perspectives*; IntechOpen: London, UK, 2023.
7. Ho, G.T.S.; Tang, Y.M.; Leung, E.K.; Tong, P.H. Integrated reinforcement learning of automated guided vehicles dynamic path planning for smart logistics and operations. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *196*, 104008. [CrossRef]
8. Fatima, Z.; Tanveer, M.H.; Waseemullah Zardari, S.; Naz, L.F.; Khadim, H.; Ahmed, N.; Tahir, M. Production plant and warehouse automation with IoT and industry 5.0. *Appl. Sci.* **2022**, *12*, 2053. [CrossRef]
9. Tong, Q.; Ming, X.; Zhang, X. The realization for automated warehouse based on the integration of ERP and WMS. In *Proceedings of the 2020 the 7th International Conference on Automation and Logistics (ICAL), Beijing, China, 22–24 July 2020*; Association for Computing Machinery: New York, NY, USA, 2020; pp. 76–80.
10. European Commission. Industry 5.0. Research and Innovation. 2024. Available online: https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en (accessed on 23 June 2025).
11. Pasham, S.D. Energy-Efficient Task Scheduling in Distributed Edge Networks Using Reinforcement Learning. *Computertech* **2019**, *7*, 248–268. [CrossRef]
12. Nweje, U.; Taiwo, M. Supply chain management: Balancing efficiency and environmental responsibility. *World J. Adv. Res. Rev.* **2025**, *25*, 1547–1564. [CrossRef]
13. Perotti, S.; Colicchia, C. Greening warehouses through energy efficiency and environmental impact reduction: A conceptual framework based on a systematic literature review. *Int. J. Logist. Manag.* **2023**, *34*, 199–234. [CrossRef]
14. Lewczuk, K.; Kłodawski, M.; Gepner, P. Energy consumption in a distributional warehouse: A practical case study for different warehouse technologies. *Energies* **2021**, *14*, 2709. [CrossRef]
15. Riazi, S.; Bengtsson, K.; Lennartson, B. Energy optimization of large-scale AGV systems. *IEEE Trans. Autom. Sci. Eng.* **2020**, *18*, 638–649. [CrossRef]
16. Maheshwari, P.; Kamble, S.; Kumar, S.; Belhadi, A.; Gupta, S. Digital twin-based warehouse management system: A theoretical toolbox for future research and applications. *Int. J. Logist. Manag.* **2024**, *35*, 1073–1106.
17. Sahara, C.R.; Aamer, A.M. Real-time data integration of an internet-of-things-based smart warehouse: A case study. *Int. J. Pervasive Comput. Commun.* **2022**, *18*, 622–644. [CrossRef]
18. Lam, H.Y.; Ho, G.T.S.; Mo, D.Y.; Tang, V. Responsive pick face replenishment strategy for stock allocation to fulfil e-commerce order. *Int. J. Prod. Econ.* **2023**, *264*, 108976. [CrossRef]
19. Mikhail, D.; Sadllah, S. A Study on Layout Design for a Logistic Center–Case Study at ASSA ABLOY Opening Solutions Sweden AB. Master's Thesis, Mälardalen University, Eskilstuna, Sweden, 2020.
20. Edouard, A.; Sallez, Y.; Fortineau, V.; Lamouri, S.; Berger, A. Automated storage and retrieval systems: An attractive solution for an Urban warehouse's sustainable development. *Sustainability* **2022**, *14*, 9518. [CrossRef]
21. Azadeh, K.; De Koster, R.; Roy, D. Robotized and automated warehouse systems: Review and recent developments. *Transp. Sci.* **2019**, *53*, 917–945. [CrossRef]
22. Plakas, G.; Aretoulaki, E.; Ponis, S.T.; Agalianos, K.; Maroutas, T.N. A proposed technology solution for enhancing order picking in warehouses and distribution centers based on a gamified augmented reality application. In Proceedings of the 14th IADIS International Conference Interfaces and Human Computer Interaction, Zagreb, Croatia, 23–25 July 2020; pp. 23–25.
23. Cirillo, V.; Rinaldini, M.; Virgillito, M.E.; Divella, M.; Manicardi, C.; Massimo, F.S.; Cetrulo, A.; Costantini, E.; Moro, A.; Staccioli, J. *Case Studies of Automation in Services*; Publications Office of the European Union: Luxembourg, 2022.
24. Roodbergen, K.J.; Vis, I.F. A survey of literature on automated storage and retrieval systems. *Eur. J. Oper. Res.* **2009**, *194*, 343–362. [CrossRef]
25. Minashkina, D.; Happonen, A. Decarbonizing warehousing activities through digitalization and automatization with WMS integration for sustainability supporting operations. *E3S Web Conf.* **2020**, *158*, 03002. [CrossRef]
26. Shabur, M.A.; Shahriar, A.; Ara, M. From automation to collaboration: Exploring the impact of industry 5.0 on sustainable manufacturing. *Discov. Sustain.* **2025**, *6*, 341. [CrossRef]
27. Cosma, A.M.I.; Zangara, G.; Silvestri, L.; Filice, L. Sustainability Impact of Automated Warehouses in Industry 4.0 scenario. *Procedia Comput. Sci.* **2025**, *253*, 3196–3205. [CrossRef]
28. Ahmed, T.; Karmaker, C.L.; Nasir, S.B.; Moktadir, M.A.; Paul, S.K. Modeling the artificial intelligence-based imperatives of industry 5.0 towards resilient supply chains: A post-COVID-19 pandemic perspective. *Comput. Ind. Eng.* **2023**, *177*, 109055. [CrossRef] [PubMed]
29. Li, L.; Duan, L. Human centric innovation at the heart of industry 5.0—Exploring research challenges and opportunities. *Int. J. Prod. Res.* **2025**, *64*, 4901–4933. [CrossRef]
30. Ferrari, A.; Zenezini, G.; Rafele, C.; Carlin, A. A Roadmap towards an Automated Warehouse Digital Twin: Current implementations and future developments. *IFAC-PapersOnLine* **2022**, *55*, 1899–1905. [CrossRef]
31. Ponis, S.T.; Efthymiou, O.K. Cloud and IoT applications in material handling automation and intralogistics. *Logistics* **2020**, *4*, 22. [CrossRef]

32. Soori, M.; Arezoo, B.; Dastres, R. Internet of things for smart factories in industry 4.0, a review. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 192–204. [CrossRef]
33. Andiyappillai, N. Factors influencing the successful implementation of the warehouse management system (WMS). *Int. J. Comput. Appl.* **2020**, *177*, 21–25. [CrossRef]
34. Li, C.H.; Lam, T.S.D.; Lo, C.K.D.; Liu, C.W. Digital Twins: Adoption in Solar Panel System Construction. In *2024 4th International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*; IEEE: New York, NY, USA, 2024; pp. 1–5.
35. Rasheed, A.; San, O.; Kvamsdal, T. Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access* **2020**, *8*, 21980–22012. [CrossRef]
36. Rajendiran, G.R.; Ayyadurai, R. Digital Twin Technology for Real-Time Simulation and Optimization of Warehouses. *N. Am. J. Eng. Res.* **2023**, *4*.
37. Wu, S.; Xiang, W.; Li, W.; Chen, L.; Wu, C. Dynamic scheduling and optimization of AGV in factory logistics systems based on digital twin. *Appl. Sci.* **2023**, *13*, 1762. [CrossRef]
38. Dai, M.; Shen, Y.; Liu, W.; Lü, M. Digital twin-based optimization of AGV scheduling under energy constraints in plant factories. *J. Clean. Prod.* **2025**, *519*, 146016. [CrossRef]
39. Félix-Cigalat, J.S.; Domingo, R. Towards a digital twin warehouse through the optimization of internal transport. *Appl. Sci.* **2023**, *13*, 4652. [CrossRef]
40. Leung, E.K.H. Total fulfillment management: Principles, practices and use cases. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *194*, 103888. [CrossRef]
41. Ho, G.T.S.; Tang, V.; Tong, P.H.; Tam, M.M.F. Demand-driven storage allocation for optimizing order picking processes. *Expert Syst. Appl.* **2025**, *272*, 126812. [CrossRef]
42. Jiang, Z.Z.; Zhao, J.; Sun, M. Joint optimization of order picking and delivery in ergonomic picking systems with due dates for sustainability and resilience. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *191*, 103727. [CrossRef]
43. Leung, E.K.; Lee, C.K.H.; Ouyang, Z. From traditional warehouses to Physical Internet hubs: A digital twin-based inbound synchronization framework for PI-order management. *Int. J. Prod. Econ.* **2022**, *244*, 108353. [CrossRef]
44. Zhang, L.; Yang, C.; Yan, Y.; Cai, Z.; Hu, Y. Automated guided vehicle dispatching and routing integration via digital twin with deep reinforcement learning. *J. Manuf. Syst.* **2024**, *72*, 492–503. [CrossRef]
45. Naumov, V.; Kubek, D.; Więcek, P.; Skalna, I.; Duda, J.; Goncerz, R.; Derlecki, T. Optimizing energy consumption in internal transportation using dynamic transportation vehicles assignment model: Case study in printing company. *Energies* **2021**, *14*, 4557. [CrossRef]
46. Chow, E.W.H.; Li, C.H.; Tang, V.; Tam, M.M.F.; Ho, G.T. Reinforcement learning-driven resilient smart Warehousing: A holistic approach for replenishment and picking. *Eng. Appl. Artif. Intell.* **2026**, *177*, 114921. [CrossRef]