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Is Warehouse Management System (WMS) Really Important? A Case Study in a Thailand's Warehouse

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Abstract

This study employs simulation modeling via Arena software to investigate strategies for optimizing operational efficiency in a manual labor-dependent inbound storage warehouse, where delays stem from challenges in storage allocation. Key issues include inefficient spatial estimation for incoming items, extended retrieval times for goods and vacant locations, and recurrent misplacement errors—problems exacerbated by high inventory volumes and the absence of real-time storage data. The simulation evaluates the existing workflow and proposes a redesigned system integrating a Warehouse Management System (WMS). The WMS framework enables real-time inventory tracking through mobile devices, utilizing item dimensions and weight data to automate storage assignments, thereby accelerating decision-making and improving accuracy. Simulation results demonstrate that WMS adoption reduces customer queue times by 62.60%, decreases externally stacked pallets by 16.35%, and allows a potential workforce reduction of 17 employees while maintaining service levels. The findings underscore the WMS's capacity to enhance operational agility, reduce labor costs, and improve responsiveness to dynamic customer demands, positioning it as a critical tool for modern warehouse optimization.

Keywords: Shelf Allocation, Warehouse Management System, Warehouse Efficiency, Simulation

INTRODUCTION

The air freight industry plays a vital role in connecting global logistics networks, and effective warehouse management is crucial to meet customer demands quickly and accurately. Many air freight service providers operate inbound warehouses that handle large volumes of goods from international users. However, traditional warehouse management methods face several challenges, including heavy reliance on manual labor, delays in locating available storage spaces due to the absence of real-time shelf data, and overflow of goods and pallets, which leads to underutilized storage areas. In today's competitive business environment, efficient supply chain management is a key driver of competitive advantage (Christopher, 2016). This research aims to optimize warehouse management by using the Arena simulation program to analyze and redesign workflow systems, along with the implementation of a Warehouse Management System (WMS). A WMS is a software solution that helps manage warehouse operations from the moment goods enter until they are shipped out (Richards, 2017). The system enables employees to check real-time shelf availability via mobile devices and assess the size and weight of products, addressing key issues in quickly and accurately selecting appropriate storage locations (Gu et al., 2007). For instance, Odoo provides free inventory and warehouse management modules (Odoo, n.d.) and offers an educational program to support system learning and implementation in academic settings.

To highlight the effectiveness of WMS, a case analysis of a warehouse in Bangkok, Thailand was conducted. This study identified several challenges in managing a temporary warehouse. A temporary warehouse is a facility used for short-term storage before goods are shipped to customers or forwarded through shipping processes. Such warehouses are commonly used in the airfreight industry to handle fluctuating demand, seasonal peaks, or unexpected supply chain disruptions (Richards, 2017). The main challenges include space constraints, a high volume of stored items, and the mixed placement of goods. Employees faced difficulties in locating items, leading to prolonged search times and errors when large items could not fit into designated storage slots. These issues stemmed from the absence of real-time data availability, forcing warehouse staff to rely on personal experience for item placement and record-keeping. As a result, operational delays increased, along with a higher likelihood of errors. Implementing a WMS offers several benefits to address these challenges. WMS improves inventory visibility, enabling real-time tracking of available storage slots and reducing the time spent searching for placement positions (Frazelle, 2002). It enhances operational efficiency by automating data collection and optimizing storage allocation based on product dimensions and weight (Richards, 2018). Additionally, WMS reduces human error in inventory management, leading to more accurate stock levels and fewer misplaced items (Emmett, 2005). By streamlining warehouse operations, the system minimizes delays, improves space utilization, and ultimately enhances overall supply chain performance. The significance of efficient warehouse management is underscored by the projected growth in air freight volumes. According to Krungsri Research (2024), air freight volume is expected to grow by 3-5% per year over the next three years**.** This anticipated increase in volume highlights the necessity for robust WMSs to handle the escalating demand effectively.

This research examines the operations of the case study warehouse using simulation techniques and explores potential solutions to enhance the efficiency of identifying vacant shelf positions. It compares the current manual method with the implementation of WMS to determine its impact on reducing goods' waiting time. The adoption of WMS in the airfreight industry is particularly crucial due to the industry's fast-paced nature and the need for real-time inventory tracking. Implementing WMS can significantly improve warehouse efficiency by automating inventory management, minimizing human errors, and expediting cargo handling processes. Additionally, it enhances space utilization by providing optimized storage recommendations and real-time data on available shelf positions. This research contributes to the understanding of how digital transformation can streamline airfreight logistics, reduce operational bottlenecks, and ultimately improve customer satisfaction by ensuring timely deliveries.

LITERATURE REVIEW

Overview of warehouse management in airfreight operations

Warehouse management is crucial for ensuring efficient logistics and supply chain operations, especially in the air freight industry, where speed and accuracy are paramount. Unlike traditional warehouses, airfreight facilities operate under strict time constraints to meet the demands of international trade and express shipping. Effective management requires real-time tracking, optimal space utilization, and rapid turnaround times to prevent cargo delays and reduce holding costs (Richards, 2017). According to Gu et al. (2007), airfreight warehouse operations involve receiving, sorting, and dispatching cargo with minimal dwell time, making a robust WMS essential for streamlining workflows. Given the complexity of handling diverse cargo types from perishable goods to hazardous materials automation can significantly enhance efficiency.

Traditional methods depend largely on manual data entry and human judgment, whereas digital approaches like WMS provide automation, traceability, and data-driven decision-making. For example, manual processes often cannot update inventory in real time, leading to search delays and inefficient use of space (Frazelle, 2016). In contrast, WMS platforms provide synchronized data across devices, enabling faster and more accurate storage allocation (Richards, 2017). Despite these advantages, many airfreight warehouses still hesitate to adopt digital systems due to concerns over cost, legacy system compatibility, and organizational inertia (Poon et al., 2009). This research addresses these pain points through simulation-based analysis, aiming to evaluate the tangible benefits of transitioning from manual to digital warehouse operations.

Issues and barriers related to WMS adoption

While WMS provides significant advantages, its adoption in the airfreight sector faces several challenges. A major obstacle is the high initial investment required, including software, hardware, and training (Helo & Szekely, 2005). Small and medium-sized operators often struggle to justify these costs.

Employee resistance is another barrier. De Koster et al. (2007) explain that warehouse staff may perceive WMS as a threat to job security or experience difficulty adapting to new systems. Integrating WMS with existing ERP or legacy systems is also technically complex, frequently leading to data silos and operational disruptions (Poon et al., 2009). These risks are particularly acute in time-sensitive environments like airfreight, where any transition-induced delay can have significant downstream effects (Frazelle, 2016). To mitigate these issues, researchers advocate for phased implementation strategies, early stakeholder engagement, and user-focused WMS design.

WMS adoption trends during and after COVID-19

The COVID-19 pandemic significantly accelerated digital transformation within the global logistics sector, underscoring the urgent need for agile and automated warehouse systems. Kumar, Singh, and

Dwivedi (2021) highlighted that the pandemic revealed major vulnerabilities in manual warehouse operations, such as labor shortages, stricter health and safety protocols, and surging e-commerce demand. These challenges pushed logistics providers to prioritize investments in technologies like WMS to enhance responsiveness and reduce human contact. Nguyen and Zhang (2022) found that companies with existing digital infrastructure—such as real-time inventory tracking and automated storage systems—demonstrated greater resilience to supply chain disruptions caused by COVID-19. Their findings emphasize that WMS adoption not only boosts efficiency but also strengthens operational resilience. Supporting this trend, a survey by the International Air Transport Association (IATA, 2021) reported a 28% increase in digital adoption among air cargo operators between 2020 and 2021, with WMS ranked among the top three most implemented systems. In a related study, Basnet et al. (2023) analyzed post-pandemic logistics trends in Southeast Asia and found that warehouses equipped with WMS experienced faster recovery times and greater scalability during periods of fluctuating demand.

Simulation techniques in warehouse optimization and airfreight challenges

Simulation techniques are widely recognized as effective tools for identifying inefficiencies and evaluating new warehouse layouts or technologies. Numerous studies have utilized platforms like Arena to model and analyze material handling processes. For example, Abedinzadeh and Reza Erfanian (2018) used Arena to identify delays in an automotive warehouse and proposed improvements through layout and resource optimization. Similarly, Liong and Loo (2009) examined loading and unloading efficiency, highlighting the impact of factors such as forklift availability and truck inter-arrival times. Beyond Arena, other simulation tools have been employed to address various warehouse challenges. Saderova et al. (2022) used EXTENDSIM8 to simulate pallet unloading operations, while Burinskiene (2015) introduced new forklift routing algorithms to enhance efficiency. Janeková (2021) applied Tecnomatix to optimize workforce allocation, and earlier work by Burinskiene (2011) demonstrated that integrating WMS with RFID technology could reduce travel distances by up to 37%. Despite these advancements, limited research has focused specifically on labor-intensive airfreight warehouses. These environments present unique challenges—such as strict air cargo regulations, the handling of diverse cargo types, and intense time pressures—that make the adoption of WMS both complex and essential.

METHODOLOGY

Phase 1: Data collection

This study focuses on evaluating the operational efficiency of a temporary warehouse in Bangkok, Thailand. Time-related metrics were recorded at various locations within the facility, while interviews with staff and clients provided insights into operational challenges. The discussions aimed to compare the existing system with WMS to identify inefficiencies and explore potential solutions to reduce errors and delays.

Phase 2: Establishment of the warehouse model

Warehouse type and operational scope

This study focuses on a temporary storage warehouse designed for the short-term holding of goods before customer pickup. Unlike distribution centers or long-term storage facilities, a temporary warehouse is defined by high inventory turnover with short dwell times, minimal automation with a reliance on manual handling processes, limited storage capacity that demands efficient space utilization, and direct customer pickup operations, where inbound and outbound logistics must be carefully synchronized to prevent congestion. The primary operations in this type of warehouse involve placing items in designated storage zones optimized for frequent movement rather than long-term holding. When a pickup request is received, goods are retrieved, verified, and staged for customer pickup.

Warehouse model development

To evaluate and enhance these operations, a warehouse simulation model was created using specialized software. This model provides a visual representation of real-world warehouse movements and accurately depicts the logical flow of inbound, storage, and outbound processes.

Key components of the model:

The model includes key components such as checkpoints for inventory verification, documentation, and repackaging, as well as simulated storage zones optimized for both fast-moving and slow-moving goods. It also defines the movement flow of material handling equipment and personnel. Using entity-based movement logic, the model represents inbound shipments, staff, forklifts, and customers as entities navigating through pathways, interacting with processing stations, and triggering warehouse activities.

Phase 3: Model validation

Model validation ensures that the simulation accurately reflects real-world operations (Kleijnen, 1995). This study employs two key validation techniques: using animation in Arena to visualize entity flow and applying statistical tests to compare simulation results with historical system performance data.

Simulation in Arena to observe entity flow

The simulation model is constructed in Arena, ensuring that all components, including entities, queues, resources, and process flows, are correctly defined. Arena's built-in animation features are activated to visualize entity movement within the system. Multiple simulation runs are conducted to observe entity behavior and movement. The observed entity flow is then compared with the workflow of the real-world system to ensure accuracy. If discrepancies arise, process parameters, routing rules, or other model elements are adjusted to better align with real-world operations.

Determination of the number of replications

The number of replications was determined based on the confidence interval approach. The objective was to achieve a desired margin of error (E) within a specified confidence level (95%). The required number of replications (N) was calculated using Equation 1 (Montgomery & Runger, 2018).

$$N = \left(\frac{Z_{\alpha/2} \cdot \sigma}{E}\right)^2 \tag{1}$$

Where:

- $Z_{\alpha/2}$ is the critical value from the standard normal distribution for a 95% confidence level (1.96)
- σ is the sample standard deviation from a pilot run,
- E is the acceptable margin of error.

Statistical analysis

To quantitatively validate the model, output data such as average wait time, processing time, and throughput are collected from the Arena simulation and compared to real-world system data. The validation process involves hypothesis testing:

- Null Hypothesis (H_0): There is no significant difference between simulation outputs and real-world data.
- Alternative Hypothesis (H_1): A significant difference exists between the two datasets.

A t-test is performed for continuous data (e.g., processing time, queue wait time) to compare mean values. A p-value is calculated and compared to a significance level ($\alpha = 0.05$):

- If p-value > 0.05, H_0 is accepted, indicating that the simulation results accurately represent real-world data.
- If p-value ≤ 0.05, H_0 is rejected, and model adjustments are made to improve accuracy. Parameters such as processing distributions and arrival rates are modified if significant discrepancies are found.

Comparison of performance results

After simulating both systems, the results were analyzed based on several criteria: comparing average waiting times across different processes, evaluating the number of items waiting at various stages, and assessing workforce requirements before and after implementing cost-reduction measures. The analysis focused on measuring labor cost savings from optimized workforce allocation, determining whether automation or process adjustments reduced labor needs, and calculating the financial benefits of these changes. This information provides decision-makers with valuable insights to evaluate the potential return on investment when considering automation technologies or process modifications.

CASE ANALYSIS

Case background and scenarios of warehouse practices

The warehouse selected for this study is a temporary air cargo storage facility located at an airport in Thailand, primarily used for short-term holding of goods awaiting customer pickup. Serving as an intermediary space, the warehouse stores items temporarily until they are retrieved by customers or delivery agents. This type of warehouse is common in industries with high turnover rates, such as retail, e-commerce, and distribution. The model utilizes real warehouse data to enhance the accuracy of operational simulations. Table 1 presents a detailed analysis of processing times using triangular distribution patterns, both before and after workflow system improvements and redesign. The triangular distribution, i.e. TRIA(), is a probability distribution applied when only the minimum, most likely, and maximum values of a process are known, but the exact shape of the distribution is unspecified.

Table 1: Two scenarios of workflow system and distribution patterns

Job	Process	Before		After	
		Distribution Patterns (min)	**Job Precedence**	**Distribution Patterns (min)**	**Job Precedence**
A	Breakdown	TRIA(5,10,15)	-	TRIA(5,10,15)	-
B	Transported to the ASRS	TRIA(3,5,8)	A	TRIA(3,5,8)	A
C	Transported to the assigned storage location	TRIA(2,4,5)	A	-	-
D	Loaded into the ASRS	TRIA(3,6,10)	B	TRIA(3,6,10)	B
E	Assigned a storage location	TRIA(5,8,13)	C	TRIA(0.5,1,1.5)	A
F	Transported to the designated shelf	TRIA(3,6,8)	E	TRIA(3,6,8)	E
G	Submit documents	TRIA(2,5,8)	-	TRIA(2,5,8)	-
H	Hands over to the warehouse front staff	TRIA(4,7,12)	G	TRIA(4,7,12)	G
I	Locates items on the shelf	Common items 95% TRIA(5,8,10), Wrong item 3% TRIA(10,15,20), Lost item 2% TRIA(15,30,50)	H	Common items 98% TRIA(2,5,7), Wrong item 1% TRIA(4,8,10), Lost item 1% TRIA(6,9,13)	H
J	Retrieves goods from the ASRS	TRIA(4,10,17)	H	TRIA(4,10,17)	H

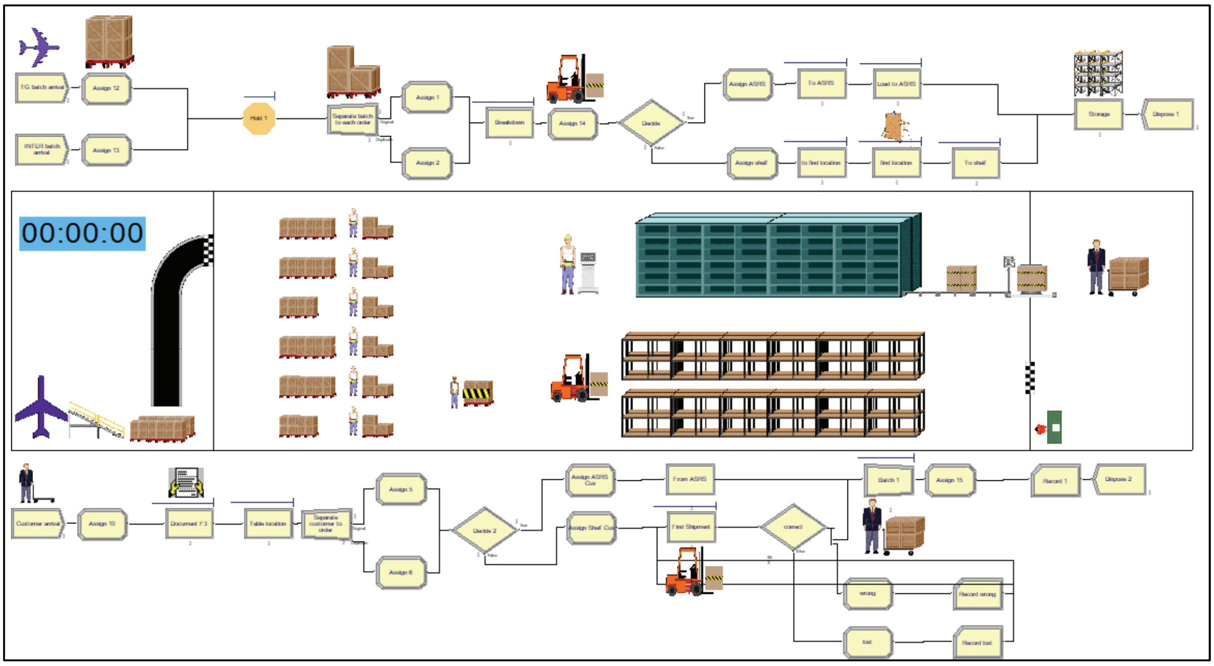
Simulation model of the warehouse

Picture 1 depicts a warehouse model with forklift travel routes, developed using specialized software. It visually represents the logical flow of warehouse operations, highlighting the movement of goods in and out of storage areas. The model integrates various interconnected components, such as processing stations, storage zones, and transportation routes, which are illustrated through modules, symbols, and pathways to represent entity transfers.

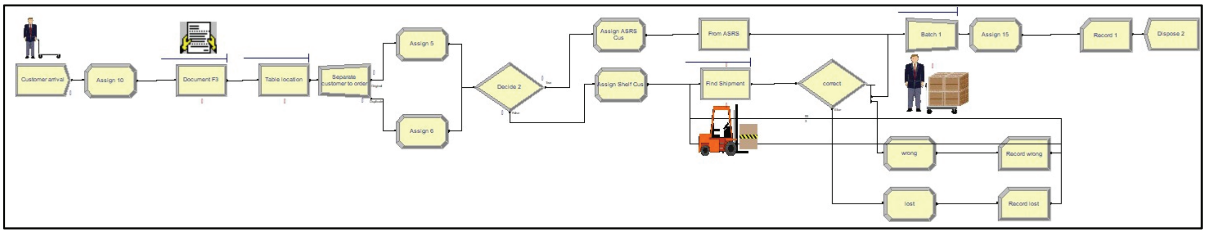
In this case study, goods moving through the warehouse system are treated as entities, with operations divided into inbound and outbound processes. As shown in Picture 2, the outbound process begins in the document room, where three employees per shift manage order receipts, verify item lists, locate goods, and print picking documents. Customers then submit these documents to the issuing staff, consisting of two employees per shift. The picking process is divided into two categories: goods stored in the Automated Storage and Retrieval System (ASRS), where customers collect their items from a designated pickup point, and goods stored on shelves, which are retrieved by six forklift operators per shift. A single-order picking method is used to ensure each order is processed individually, improving both accuracy and efficiency.

In Picture 3, the inbound process begins with goods being placed in a temporary holding area before being moved to the sorting zone, where six employees per shift sort them based on purchase orders. Similar to the outbound process, the warehouse classifies goods into two categories: ASRS-designated goods, which forklift operators transport to the ASRS under the supervision of three employees per shift, and shelf storage goods, which forklift operators move to designated storage locations.

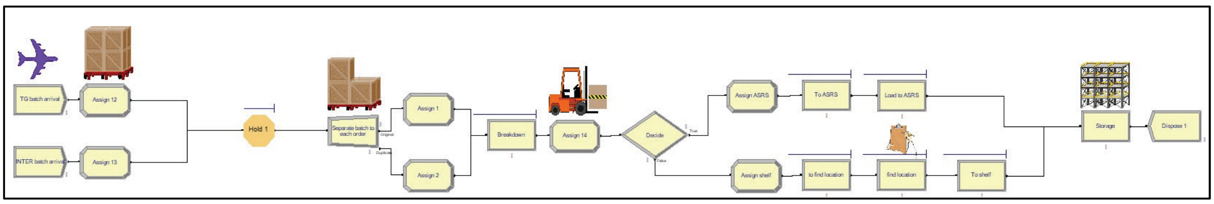
Picture 1: The model of the warehouse and forklift travel routes



Picture 2: The outbound process



Picture 3: The inbound process



Model Evaluation and Validation

Number of replications needed

The simulation revealed that the estimated standard deviation (σ) of the key performance measure, average waiting time, was 69.96. Given a desired margin of error of 14.84, based on industry-accepted tolerances for customer queue times, the required number of replications was calculated as:

$$N = \left(\frac{1.96 \times 69.96}{14.84}\right)^2 = 86$$

As a result, 86 replications were performed to ensure statistical reliability. A warm-up period was not needed, as the simulation model assumed a stable and continuous inflow of items from the outset, with no significant transient start-up effects observed.

Entity flow analysis and process optimization

The use of animation effectively demonstrated the movement of entities, enabling the identification of inefficiencies such as congestion points and incorrect routing. During observations, it was noted that some entities bypassed a process step due to incorrect decision logic, which was subsequently corrected. Additionally, the model's queue buildup closely mirrored real-world observations, confirming the accuracy of process times and resource availability. Adjustments to the processing logic eliminated unintended entity looping, resulting in a more accurate and improved simulation model. By leveraging animation, modelers were able to visually confirm that the simulated workflow adhered to the intended design, making it an effective first step in validation.

Statistical validation and model refinement

A two-sample t-test was performed to compare the mean values between the real-world system and the Arena simulation. As shown in Table 2, the p-value (0.814) is greater than 0.05, leading us to fail to reject the null hypothesis. This suggests that there is no statistically significant difference between the real-world system and the simulation model, indicating that the Arena simulation accurately reflects the actual system. Therefore, no immediate adjustments to the model parameters are needed based on this validation test.

Table 2: Independent sample t-test result

Test	**Value**
Null Hypothesis	$H_0 : \mu_1 - \mu_2 = 0$
Alternative Hypothesis	$H_0 : \mu_1 - \mu_2 \neq 0$
T-Value	-0.24
Degrees of Freedom (DF)	7
p-Value	0.814

RESULTS AND DISCUSSION

The simulation evaluates and compares average waiting times for picking and storing goods based on product types in customer orders. It contrasts the current workflow with the projected outcomes following the implementation of a Warehouse Management System (WMS). A summary of the results is shown in Table 3. The findings reveal significant reductions in waiting times across various processes, highlighting the efficiency gains enabled by the WMS. The most notable improvement is in customer waiting time for goods, which drops from 40.15 minutes to 6.72 minutes—an 83.26% reduction. Overall order fulfillment time also improves substantially, falling from 69.96 minutes to 29.26 minutes (a

58.18% decrease). While improvements in product handling are more modest, there is a dramatic 91.17% decrease in the time products wait to be transported to the Automated Storage and Retrieval System (ASRS). These results are consistent with prior studies. For example, Chang et al. (2020) reported a 50–80% reduction in order processing times following WMS adoption, while Kim & Lee (2021) observed a 60% decrease in storage and retrieval durations with ASRS. Similarly, Smith et al. (2019) found that WMS implementation led to a 70% improvement in overall warehouse efficiency.

Table 3: Comparison of average waiting time in processes: current vs. wms implementation

Process	Average Waiting Time (min)		
	Current	WMS	Reduction (%)
Customer document submission	0.01	0.01	0.00
Customer document submission for goods retrieval	0.36	0.35	2.78
Customer waiting time for goods	40.15	6.72	83.26
Total time for the customer to receive all goods	69.96	29.26	58.18
Product waiting for picking	9.89	9.87	0.20
Product waiting for transport to ASRS	31.61	2.79	91.17
Product waiting to be loaded into ASRS	6.13	2.41	60.69
Product waiting to be placed on shelves	28.65	2.75	90.40

Table 4 summarizes changes in queue lengths for picking and storing goods. Post-WMS implementation, queue lengths are significantly reduced, particularly in customer wait times and product handling. The average number of customers waiting for goods drops from 14.52 to 2.27, an 84.37% reduction. Although pallet movement and sorting saw only slight improvements, the number of pallets awaiting shelf placement decreased dramatically—from 22.16 to 2.14 (a 90.34% reduction). This demonstrates the WMS's ability to streamline transport coordination and scheduling while enhancing ASRS integration. These outcomes align with previous findings. Zhou et al. (2021) observed an 80% reduction in customer queue lengths after WMS implementation, closely matching the 84.37% reduction found here. Gonzalez & Ramirez (2020) noted a 65–85% drop in storage and retrieval queues with WMS-ASRS integration, consistent with this study's 86.89% and 90.34% reductions. Lee et al. (2019) also highlighted a 50% decrease in warehouse congestion due to improved material flow and space utilization from WMS deployment.

Table 4: Comparison of queue length in processes

Process	Number Waiting in Queue		
	Current	WMS	Reduction (%)
The average number of customers waiting for goods (people)	14.52	2.27	84.37
Total pallets waiting for picking	177.95	167.54	5.85
Total pallets waiting for sorting	12.80	12.78	0.16
Total pallets waiting for transport to ASRS	16.32	2.14	86.89
Total pallets waiting to be loaded into ASRS	3.15	1.25	60.32
Total pallets waiting to be placed on shelves	22.16	2.14	90.34

Finally, workforce cost evaluations show significant labor savings. By reducing waiting times and optimizing task allocation, the required workforce drops from 24 to 17 employees—a 28.33% reduction—resulting in annual labor cost savings of 2,482,000 THB (Table 5). These findings support Richards (2018), who emphasized WMS's role in improving efficiency and reducing errors. Fernie and Sparks (2019) reported a 30% reduction in manual handling needs when combining WMS with ASRS, and Baker and Halim (2021) found digital systems can reduce administrative and transport staff by up to 40%, consistent with the reduced labor needs seen in this study. Although this study focuses on a case in the airfreight logistics sector, the framework and methodology are adaptable to other industries facing similar warehousing challenges—such as e-commerce, automotive parts, and cold chain logistics. Overall, the findings highlight the strategic value of WMS in improving operational efficiency, lowering costs, and enabling faster, more accurate responses to evolving customer demands.

Table 5: Employee count comparison: current vs. WMS implementation

Department	Number of Employees		
	Current	**WMS**	**Reduction (%)**
Documents processing	9	3	66.67
Document submission for goods receiving	6	3	50.00
Product sorting	18	18	0.00
Loading goods into ASRS	9	8	11.11
Goods transportation	18	11	38.89
Total number of employees	60	43	28.33

CONCLUSIONS

This study aimed to enhance the operational efficiency of inbound warehouse processes in a labor-intensive environment, where delays are often caused by manual storage allocation, limited visibility of available space, and frequent placement errors. Using simulation modeling in Arena, the current warehouse workflow was compared with a redesigned system featuring a Warehouse Management System (WMS). The results show that implementing a WMS can reduce customer wait times by 62.60%, decrease pallet congestion at the warehouse front by 16.35%, and allow for a potential workforce reduction of up to 17 employees without compromising service quality. In addition to operational improvements, WMS adoption also brings cost-saving benefits—such as lower labor expenses and better space utilization—supporting a shorter payback period and higher return on investment. These findings underscore the financial and strategic viability of digital transformation, particularly for facilities under pressure to optimize resources while maintaining high service standards.

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