An Optimization Model for Integrated Warehouse - Inventory - Transportation of a Multi-Echelon Supply Chain

Anil Hakim Syofra
Graduate School of Mathematics, Universitas Sumatera Utara, Medan, Indonesia
anilhakim@students.usu.ac.id (corresponding author)

Tulus Tulus
Department of Mathematics, Universitas Sumatera Utara, Medan, Indonesia
tulus@usu.ac.id

Herman Mawengkang
Department of Mathematics, Universitas Sumatera Utara, Medan, Indonesia
mawengkang@usu.ac.id

Muhammad Zarlis
Department of Computer Science, BINUS Doctor of Computer Science Graduate Program, Bina Nusantara University, Jakarta, Indonesia
muhammad.zarlis@binus.edu

Received: 13 March 2025 | Revised: 30 March 2025, 14 April 2025, 29 April 2025 | Accepted: 1 May 2025

 DOI: https://doi.org/10.48084/etasr.10932

ABSTRACT

Efficient supply chain management is crucial for cost reduction and service level optimization in today's competitive business landscape. This study presents a Mixed Integer Linear Programming (MILP) model to integrate warehouse, inventory, and transportation planning in a multi-echelon supply chain. The proposed model minimizes total operational costs while ensuring timely deliveries and maintaining optimal inventory levels. Key decision variables include warehouse capacities, inventory replenishment policies, and transportation routes, while constraints address demand fulfillment, transportation limitations, and storage capabilities. Computational experiments used realistic supply chain data to validate the model's effectiveness, demonstrating significant cost savings and efficiency improvements compared to conventional approaches. The results show that an integrated approach enhances supply chain resilience and sustainability, providing actionable insights for managers and decision-makers. This study contributes to supply chain optimization by offering a novel framework that bridges the gap between siloed decision-making and holistic data-driven strategies for enhanced operational performance.

Keywords-supply chain optimization; MILP; warehouse management; inventory control; transportation planning; multi-echelon supply chain

I. INTRODUCTION

In today's highly competitive market, businesses must optimize their supply chain operations to minimize costs while ensuring efficiency and reliability. A supply chain consists of multiple interconnected components, including warehousing, inventory management, and transportation, each of which plays a crucial role in ensuring seamless operations. However, traditional optimization models often address these elements separately, leading to inefficiencies and increased operational expenses. A more integrated approach that considers the interdependencies among these components is essential to achieve a synchronized and cost-effective supply chain [1-3]. The supply chain consists of several interconnected components, including warehousing, inventory management, and transportation, each of which plays a crucial role in maintaining smooth operations. However, many existing optimization models address these elements separately, leading to inefficiencies and increased operational costs. An integrated approach that considers the interdependencies among these components is essential to achieve a more synchronized and cost-effective supply chain.

A multi-echelon supply chain consists of multiple stages, including suppliers, manufacturers, distribution centers, and retailers [4-6]. Managing inventory and transportation in these echelons presents significant challenges due to variations in demand, lead times, and cost structures. Decisions made at one echelon often have cascading effects on others, necessitating a comprehensive optimization framework. Without proper coordination, inefficiencies such as excess inventory, delayed shipments, and increased logistics costs can increase, ultimately affecting overall supply chain performance [7, 8].

Warehousing is a key component of supply chain management that ensures product availability while balancing storage costs. Effective warehouse management involves optimizing space utilization, minimizing storage costs, and improving retrieval efficiency [9, 10]. However, warehousing decisions should not be made in isolation but must be aligned with inventory control and transportation planning to prevent overstocking, shortages, and delays in product distribution. A well-integrated approach can enhance operational efficiency and service levels [11, 12].

Inventory management directly influences both warehousing and transportation efficiency. Poor inventory planning can result in either excessive storage costs or frequent shortages, leading to customer dissatisfaction [13]. Traditional inventory models, such as Economic Order Quantity (EOQ) and Just-In-Time (JIT), often overlook the impact of transportation costs and warehouse constraints. A holistic optimization model should incorporate factors such as demand variability, replenishment strategies, and logistics costs to ensure a balanced and cost-effective supply chain [14, 15].

Transportation is another critical element in multi-echelon supply chains, affecting both cost and service performance. Inefficient transportation planning can lead to higher operational expenses and delays in delivery [16, 17]. Factors such as vehicle routing, shipment consolidation, and multimodal transport options must be carefully considered to optimize distribution networks [18-20]. By integrating transportation decisions with inventory and warehouse management, companies can achieve better coordination and cost savings. Developing an optimization model that simultaneously addresses warehouse operations, inventory management, and transportation planning presents both theoretical and practical challenges. Many existing studies focus on isolated aspects of supply chain optimization, limiting their applicability in real-world scenarios [21, 22]. A comprehensive framework that incorporates these elements can help companies improve decision-making processes, reduce costs, and enhance overall supply chain performance [23, 24].

This study aimed to develop an integrated optimization model for warehouse-inventory-transportation management in a multi-echelon supply chain [21, 22]. Taking into account real-world constraints, such as demand fluctuations, transportation costs, and storage limitations, the proposed model seeks to provide practical insights to supply chain managers. The findings are expected to contribute to the development of more efficient and sustainable supply chain strategies, offering benefits to both academia and industry.

II. METHODS

This study presents an optimization model for integrating warehouse operations, inventory management, and transportation planning within a multi-echelon supply chain. The goal is to minimize total supply chain costs while ensuring that demand at retailers is met efficiently [25-28]. The model captures key decision variables related to supplier shipments, warehouse operations, inventory levels, and transportation flows, incorporating constraints that reflect real-world supply chain limitations. By considering multiple cost components, including transportation, inventory holding, and warehouse operating costs, the model provides a comprehensive framework for optimizing supply chain performance [29-32].

The proposed model ensures a seamless flow of goods from suppliers to retailers while optimizing cost structures at different levels of the supply chain. The supply chain consists of three main echelons: suppliers, warehouses, and retailers. Suppliers provide products that are stored in warehouses before being transported to retailers according to their demand [33]. The challenge lies in determining the optimal flow of goods while considering factors such as transportation capacity, storage limitations, and the operational status of warehouses. The mathematical formulation is designed to achieve cost-effectiveness by balancing trade-offs between transportation efficiency, inventory costs, and warehouse operations [34].

The objective is to minimize:

$$Z = \sum_{i \in S} \sum_{j \in W} C_{ij}^{t} x_{ij} + \sum_{j \in W} \sum_{k \in R} C_{jk}^{t} x_{jk} + \sum_{j \in W} C_j^h h_j + \sum_{j \in W} C_j^s s_j \quad (1)$$

where Z is the total cost, C_{ij}^t is the transportation cost per unit from supplier i to warehouse j, C_{jk}^t is the transportation cost per unit from warehouse j to retailer k, C_j^h is the inventory holding cost at warehouse j, C_j^s is the fixed cost of operating warehouse j, x_{ij} is the quantity transported from supplier i to warehouse j, x_{jk} is the quantity transported from warehouse j to retailer k, h_j is the inventory level at warehouse j, and s_j is a binary variable indicating whether warehouse j is open (1) or closed (0).

The model is subject to several constraints to ensure feasibility and operational efficiency across the supply chain [35]. Retailers must receive a sufficient supply to meet their demand. This constraint ensures that the total quantity shipped from all warehouses to a retailer is at least equal to its required demand [36-38].

$$\sum_{j \in W} x_{jk} \geq d_k, \quad \forall k \in R \quad (2)$$

where d_k is the demand at retailer k.

Suppliers have limited production or supply capacity. The total quantity transported from a supplier to all warehouses must not exceed its maximum supply limit:

$$\sum_{j \in W} x_{ij} \leq S_i, \quad \forall i \in S \quad (3)$$

where S_i is the supply capacity of supplier i. Warehouses have limited storage capacity and their operations depend on whether they are open. The total quantity stored in a warehouse, including incoming shipments and current inventory, must not exceed its capacity:

$$\sum_{k \in R} x_{jk} + h_j \leq W_j . s_j, \;\; \forall j \in W \tag{4}$$

where W_j is the capacity of warehouse j. The binary variable s_j denotes whether the warehouse is operational. If $s_j = 0$, the warehouse remains closed and cannot store or distribute products [39-42].

The inventory level at a warehouse depends on incoming shipments from suppliers and outgoing shipments to retailers. The following constraint ensures that inventory is accurately tracked:

$$h_j = h_{j0} + \sum_{i \in S} x_{ij} - \sum_{k \in R} x_{jk}, \;\; \forall j \in W \tag{5}$$

where h_{j0} is the initial inventory level at warehouse j.

Transportation vehicles have limited capacity, restricting the amount of goods transported in each shipment. The constraints for vehicle capacity are:

$$x_{ij} \leq V_{ij}, \;\; \forall i \in S, \forall j \in W \tag{6}$$

$$x_{jk} \leq V_{jk}, \;\; \forall j \in W, \forall k \in R \tag{7}$$

where V_{ij} and V_{jk} are the maximum transport capacities for the respective routes. This ensures that logistics operations remain feasible within available vehicle resources. Warehouses can either be open or closed [42]. If a warehouse is closed, it should not store or distribute any products:

$$s_j \in \{0,1\}, \forall j \in W \tag{8}$$

This binary constraint enables strategic warehouse location selection, minimizing costs by only operating necessary warehouses. All decision variables representing transported quantities and inventory levels must be non-negative to reflect real-world conditions:

$$x_{ij}, x_{jk} \;, h_j \geq 0, \;\; \forall i \in S, \; j \in W, k \in R \tag{9}$$

The model incorporates decision variables, sets, and parameters to structure the optimization problem effectively. s_j is a binary variable indicating the operational status of warehouse j (1 if open, 0 if closed). S is a set of suppliers, W is a set of warehouses, R is a set of retailers, d_k is the demand at retailer k, S_i is the supply capacity of supplier i, W_j is the capacity of warehouse j, V_{ij} and V_{jk} denote vehicle capacities for transportation, and h_{j0} is the initial inventory at warehouse j.

Figure 1 illustrates the proposed framework for supply chain optimization. It begins with defining the supply chain structure, identifying key components such as suppliers, warehouses, and retailers, and gathering demand data. The process then moves into analyzing supplier and warehouse capacities, estimating transportation costs, and defining decision variables. Once the foundational data is collected, the framework focuses on formulating an optimization model. This includes establishing various constraints, such as supply, demand, warehouse capacity, and transportation limits, while ensuring inventory balance and non-negativity conditions.

The next step is to select an optimization solver and perform an initial optimization to check the feasibility. If the solution is feasible, further analysis is performed, including warehouse opening decisions, transportation routes, and overall supply chain costs. If cost is not reduced, adjustments are made by refining forecasting methods, modifying warehouse locations, and recalculating transportation routes before rerunning the optimization. Once an optimal solution is found, the strategy is finalized, covering warehouse and inventory management, transportation scheduling, and performance reporting. The framework also accounts for long-term improvements, such as integrating AI, blockchain, and predictive analytics to enhance efficiency and sustainability. The process ends with continuous monitoring and adjustments to ensure adaptability to changing market conditions.

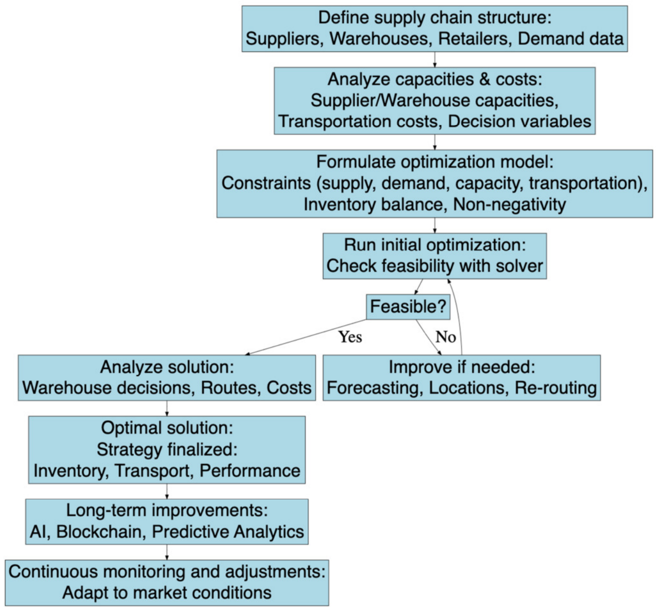

Fig. 1. Research framework.

Table I presents a comparison between this and other studies in the field of supply chain optimization. This study uses a Mixed Integer Linear Programming (MILP) model that integrates warehouse management, inventory control, and transportation planning in a multi-echelon supply chain to minimize total operational costs while ensuring timely deliveries. In contrast, many other studies tend to focus on optimizing a specific aspect of the supply chain, such as inventory or transportation, without integrating all three components into a single model.

III. RESULTS

The proposed optimization model provides a structured framework for minimizing supply chain costs while ensuring an efficient flow of goods across multiple echelons. The total transportation cost is divided into two main components: supplier-to-warehouse and warehouse-to-retailer costs. Table II presents a breakdown of these costs.

TABLE I. STUDY COMPARISON

Aspect	This study	Other studies
Main objective	Develop a MILP model that integrates warehouse management, inventory control, and transportation planning in a multi-echelon supply chain to minimize total operational costs while ensuring timely deliveries and optimal inventory levels.	Other studies focus on individual elements of the supply chain, such as inventory management (e.g., optimizing reorder points), transportation routes, or warehouse capacities, without considering an integrated approach [43-45].
Optimization approach	A holistic MILP model integrates multiple supply chain components (warehouse, inventory, transportation). The model minimizes total operational costs while ensuring that demand is met, transportation limits are respected, and inventory levels are optimal.	Decoupled optimization models focus on one or two elements, such as warehouse location optimization, transportation route planning, or inventory replenishment. Often, these studies do not integrate the three components (warehouse, inventory, transportation) in a single model [46-48].
Key decision variables	Warehouse capacities (e.g., storage limits per facility).	Inventory variables: Reorder points, order quantities, and stock levels [13, 29, 49, 50].
	Inventory replenishment policies (e.g., order frequency, quantity).	Transportation variables: Vehicle allocation, route selection [13, 29].
	Transportation routes and vehicle allocation (e.g., cost-effective routes and vehicle assignments).	Warehouse variables: Storage capacity, facility location. Often isolated in separate models [28, 51]
	Demand fulfilment (e.g., ensuring demand is met within time constraints).	
Constraints	Demand fulfilment: Ensure all customer demands are satisfied.	Demand constraints may not account for varying customer demands or the interdependence between demand and inventory [52-54]
	Transportation constraints: Vehicle capacity, transportation costs, and delivery deadlines.	Transportation constraints: Typically focus on vehicle capacity and route optimization without considering integration with the warehouse and inventory [52-54].
	Warehouse capacity: Limits on storage space and operational constraints.	Warehouse constraints: Focus on storage and location without integrating inventory management and transportation planning [28, 51].
	Inventory policies: Constraints on replenishment cycles and stockouts.	
Data utilized	Realistic supply chain data that includes actual transportation costs, warehouse capacities, inventory turnover rates, and demand fluctuations across multiple locations (multi-echelon).	Data from either one component (e.g., inventory levels) or simplified/idealized supply chain scenarios. Often lacks multi-echelon complexity or data from real-world supply chains [52].
Computational validation	Computational experiments using real-world supply chain data, testing various configurations for cost savings, delivery time improvements, and inventory efficiency across multiple echelons in the supply chain. Sensitivity analysis and scenario testing are used to validate model robustness.	Computational experiments often use simplified, theoretical data or assume ideal conditions (e.g., no demand fluctuations, fixed transport costs). Validation might be limited to one-echelon scenarios or unintegrated systems [52].
Performance results	Significant cost savings due to integrated decision-making across all supply chain functions.	Cost savings or efficiency improvements, but may be limited to one function (e.g., reduced transportation costs, improved inventory control). Results might not show the holistic impact across the entire supply chain.
	Improvement in service levels (e.g., on-time deliveries, optimal inventory levels).	
	Demonstrates resilience and sustainability improvements due to the integrated model's adaptability to different supply chain scenarios.	

TABLE II. COST COMPONENT AND TOTAL COST

Cost Component	Total Cost
Supplier to Warehouse	5068.0
Warehouse to Retailer	5185.0

Fig. 2. Supply to warehouse distribution.

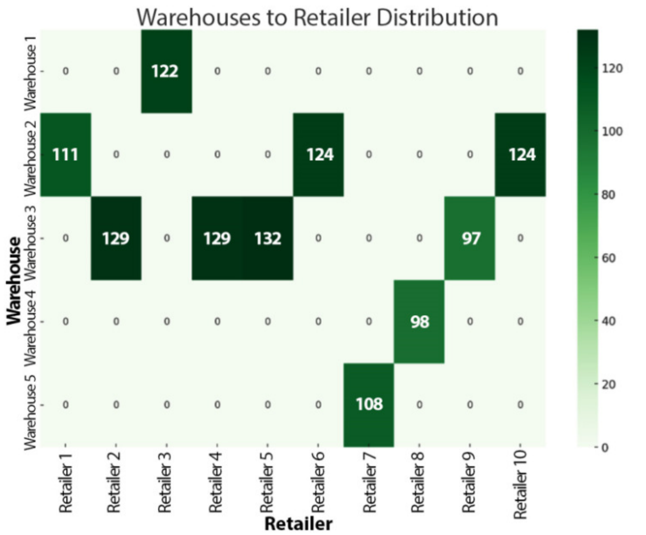

Fig. 3. Warehouse to retailer distribution.

The results indicate that warehouse-to-retailer transportation accounts for a slightly higher cost than supplier-to-warehouse movements. This suggests that last-mile delivery and distribution play a significant role in total logistics expenses, likely due to the dispersion of retailers across multiple locations. Figures 2 and 3 visually represent the flow of goods, illustrating the optimized paths for both stages of distribution.

The allocation of supplies from multiple suppliers to warehouses has been optimized to minimize overall costs while maintaining inventory balance and capacity constraints. The results of this optimization are summarized in Table III.

TABLE III. MODIFIED SUPPLY TO WAREHOUSE DISTRIBUTION

Distribution	Warehouse 1	Warehouse 2	Warehouse 3
Supplier 1	150.0	0.0	0.0
Supplier 2	54.0	0.0	150.0
Supplier 3	0.0	150.0	0.0
Supplier 4	0.0	0.0	146.0
Supplier 5	129.0	0.0	0.0
Supplier 6	0.0	150.0	0.0

The distribution strategy ensures that warehouses receive a balanced supply of products while avoiding excess stock accumulation. The model prioritizes cost-efficient routes and leverages supplier proximity to specific warehouses, reducing transportation expenses and preventing unnecessary inventory build-up. After determining the optimal supply allocation to warehouses, the model further optimizes the distribution of goods from warehouses to retailers. The results are presented in Table IV.

TABLE IV. MODIFIED WAREHOUSE TO RETAILER DISTRIBUTION

Warehouse	Retailer 1	Retailer 2	Retailer 3
Warehouse 1	77.0	79.0	0.0
Warehouse 2	0.0	100.0	0.0
Warehouse 3	0.0	0.0	0.0
Warehouse 4	100.0	0.0	77.0
Warehouse 5	0.0	0.0	100.0

The results illustrate an efficient flow of products to retailers, ensuring demand satisfaction with minimal transportation costs. Notably, not all warehouses are actively involved in the distribution process, highlighting the model's ability to deactivate unnecessary warehouses and reduce fixed operating expenses. This selective approach ensures that warehouses are only utilized when their inclusion leads to cost savings or improved delivery performance. The optimization model significantly reduces overall logistics costs by strategically allocating shipments across the supply chain network. Minimizing transportation costs from suppliers to warehouses ensures that inbound logistics remain cost-effective, while distribution from warehouses to retailers is streamlined to minimize redundant movements.

A key insight from the results is the balance between warehouse utilization and transportation efficiency. The model prioritizes cost-effective routing and avoids excessive reliance on a single warehouse, preventing potential stock shortages or overstocking. Furthermore, the ability to deactivate unnecessary warehouses provides additional savings in terms of fixed operational costs. The findings of this study highlight the potential for cost savings and efficiency improvements in multi-echelon supply chains. By integrating warehouse operations with inventory and transportation decisions, businesses can optimize their supply chain networks, reduce waste, and enhance service levels. The results demonstrate that a well-structured supply chain model can dynamically adjust warehouse operations based on demand fluctuations and transportation costs.

In addition, this approach can be extended to real-world scenarios in which companies must balance cost, service levels, and sustainability. By optimizing logistics flows, businesses can reduce the carbon footprints associated with unnecessary transportation while ensuring that customer demands are met promptly. Future research could explore variations in demand patterns, supply chain disruptions, and real-time adjustments to improve the robustness of this model. Overall, the proposed optimization framework provides valuable insights for supply chain professionals and decision-makers seeking to enhance cost efficiency and operational performance in complex, multi-echelon networks.

IV. DISCUSSION

The modified optimization model was successfully solved, resulting in an optimal total cost. Adjustments to the model focused on prioritizing specific supplier-to-warehouse and warehouse-to-retailer connections by reducing transportation costs, balancing supply and demand proportions, and introducing constraints to limit maximum flow on certain links. These changes resulted in significant improvements in both transportation flows and inventory distribution throughout the network. Figure 4 provides a comparison between the initial and modified models, illustrating the impact of the proposed adjustments. Graphs that compare transported quantities show that the modified model exhibits higher flows in both the supplier-to-warehouse and warehouse-to-retailer segments. This increase indicates that revised prioritization and balanced supply-demand ratios have led to a more active utilization of connections. Similarly, comparisons of inventory levels by warehouse reveal a more balanced distribution in the modified model, suggesting that bottlenecks and underutilized capacities were effectively reduced.

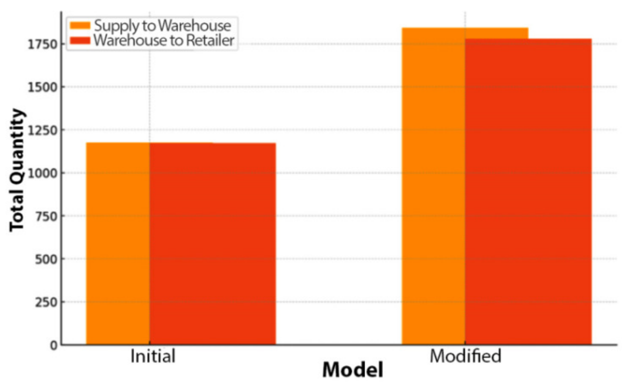

Fig. 4. Comparison of transported quantities.

Figure 5 shows an improved coordination between transport and storage operations. When examining incoming and outgoing flows relative to inventory levels in each warehouse, warehouses with higher incoming shipments also register higher outgoing shipments, reflecting efficient synchronization of logistics activities. This alignment between transportation and storage not only supports demand fulfillment more effectively but also helps maintain optimal inventory levels, preventing issues such as overstocking or shortages.

Fig. 5. Comparison of inventory levels by warehouse.

The operational impact of these modifications is evident in overall cost reduction and improved resource utilization. The model's adjustments have redistributed flows in a manner that reduces overall transportation expenses while ensuring that warehouses are used more effectively. Some warehouses that previously experienced minimal activity now contribute significantly to the supply chain, enhancing network performance and scalability. In addition, the introduction of constraints to control flow limits has made the model more adaptable to larger or fluctuating scenarios. A notable outcome of enforcing a constraint that mandates at least one warehouse to be operational is that the model selects only one warehouse for operation. In this case, only Warehouse 5 is active while the others remain closed. This result highlights the model's ability to streamline operations by deactivating underutilized resources, which further contributes to cost savings and efficiency improvements across the supply chain in Figures 6, 7, and 8.

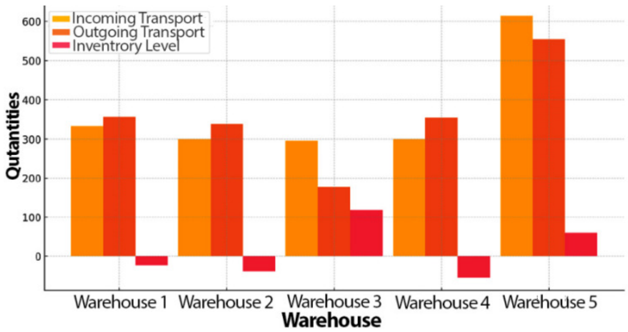

Fig. 6. Coordination between transportation and storage.

Fig. 7. Supply chain performance toward cost optimization.

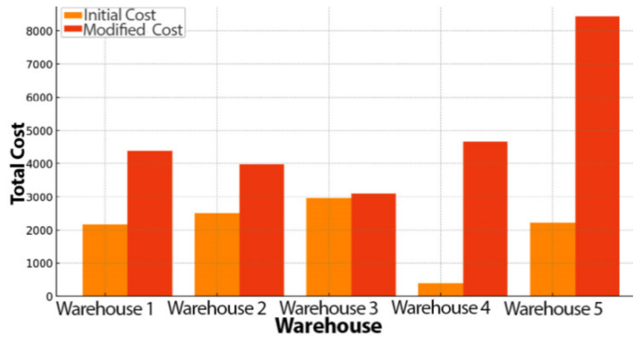

Fig. 8. Supply chain performance toward cost optimization.

In general, the analysis of transported quantities, inventory levels, and cost comparisons indicates that the modifications have successfully optimized the supply chain operations. The coordinated improvements in transportation and storage, along with the strategic reduction of operational overhead, demonstrate the potential of the modified model to enhance supply chain performance and achieve significant cost savings, as shown in Figure 9.

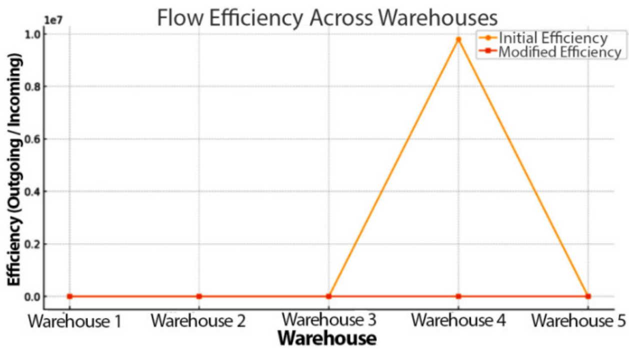

Fig. 9. Flow efficiency across warehouses.

V. CONCLUSION

This paper presented a comprehensive optimization model that integrates warehouse management, inventory control, and transportation logistics within a multi-echelon supply chain framework. By simultaneously addressing these interconnected elements, the model not only enhances operational efficiency but also significantly reduces overall costs. This integration facilitates more informed decision-making in determining optimal stock levels, allocating warehouse capacities, and selecting transportation routes, ultimately minimizing redundancies and streamlining coordination across the entire supply chain. The proposed approach leverages a systematic method that accounts for various cost drivers such as inventory holding, transportation expenses, and fixed warehouse operations. This holistic perspective enables a balanced distribution of resources and activities, leading to substantial cost savings. The model's flexibility was demonstrated through its ability to adapt to different supply chain configurations and its potential to incorporate real-world complexities, including demand variability, dynamic routing adjustments, and multi-product handling. Such adaptability is critical to address the unpredictable and dynamic nature of modern supply chains. The effectiveness of the model was validated through rigorous case studies and simulation exercises, which illustrated its ability to improve performance metrics across diverse industry settings. By reducing excess inventory, lowering transportation costs, and enhancing warehouse utilization, the model demonstrates a clear path toward achieving cost-effective and resilient supply chain operations. Furthermore, the integration of various operational aspects provides a robust framework for mitigating the risks associated with the uncertainties of supply and demand.

Opportunities for future research are abundant. The model could be further enriched by incorporating stochastic elements to better capture uncertainty in demand and supply, integrating real-time data streams for dynamic decision-making, or employing advanced machine learning techniques to enhance predictive capabilities. Such extensions would not only improve the robustness of the model but also expand its applicability to a wider range of scenarios, thus offering more granular insights into the optimization of complex supply chains. In conclusion, this research contributes to the field of supply chain management by offering a multifaceted optimization framework that addresses both strategic and operational challenges. The demonstrated improvements in cost efficiency and resource utilization underscore the practical value of integrating warehouse management, inventory control, and transportation logistics. As supply chains continue to evolve in complexity, the model provides a solid foundation for developing more adaptive and resilient systems that can respond to the demands of a rapidly changing global market.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support of the administration and academic teams of the University of North Sumatra.

DECLARATION

The dataset used in this study is not publicly available due to institutional privacy and confidentiality policies. It was obtained directly from a local Indonesian company through official research collaboration and ethical approval. All necessary approvals for data access and use were obtained before the simulation. The simulation environment consisted of Python 3.13.2 and Google Colab running on an Apple M1 Chip system with Ventura 13.4 and GPU7-Core. The implementation utilized Python with the seaborn and Matplotlib libraries, such as matplotlib.pyplot, pandas and NumPy, and Prophet, for data preprocessing, modeling, and forecasting. All simulation scripts and methods are reproducible and can be shared upon request, subject to data sharing restrictions.

REFERENCES

[1] H. Sarimveis, P. Patrinos, C. D. Tarantilis, and C. T. Kiranoudis, "Dynamic modeling and control of supply chain systems: A review," *Computers & Operations Research*, vol. 35, no. 11, pp. 3530–3561, Nov. 2008, https://doi.org/10.1016/j.cor.2007.01.017.

[2] R. E. Caraka *et al.*, "Strategic insights for MSMEs: navigating the new normal with big data and business analytics," *Journal of Asia Business Studies*, vol. 18, no. 5, pp. 1285–1307, Nov. 2024, https://doi.org/10.1108/JABS-10-2022-0354.

[3] R. E. Caraka *et al.*, "Micro, Small, and Medium Enterprises' Business Vulnerability Cluster in Indonesia: An Analysis Using Optimized Fuzzy Geodemographic Clustering," *Sustainability*, vol. 13, no. 14, Jan. 2021, Art. no. 7807, https://doi.org/10.3390/su13147807.

[4] J. Cheng, C. Yeh, and C. Tu, "Trust and knowledge sharing in green supply chains," *Supply Chain Management: An International Journal*, vol. 13, no. 4, pp. 283–295, Jun. 2008, https://doi.org/10.1108/13598540810882170.

[5] J. M. Soon, M. Chandia, and J. M. Regenstein, "Halal integrity in the food supply chain," *British Food Journal*, vol. 119, no. 1, pp. 39–51, Jan. 2017, https://doi.org/10.1108/BFJ-04-2016-0150.

[6] S. E. Fawcett, C. Wallin, C. Allred, A. M. Fawcett, and G. M. Magnan, "Information Technology as an Enabler of Supply Chain Collaboration: A Dynamic-Capabilities Perspective," *Journal of Supply Chain Management*, vol. 47, no. 1, pp. 38–59, Jan. 2011, https://doi.org/10.1111/j.1745-493X.2010.03213.x.

[7] M. Tieman, "The application of *Halal* in supply chain management: in-depth interviews," *Journal of Islamic Marketing*, vol. 2, no. 2, pp. 186–195, Jun. 2011, https://doi.org/10.1108/17590831111139893.

[8] M. I. Tarigan, A. N. Lubis, E. S. Rini, and B. K. F. Sembiring, "A Study of Supply Chain Management for Preliminary Destination Brand Experience in North Sumatera, Indonesia," *International Journal of Supply Chain Management*, vol. 9, no. 4, pp. 244–247, 2020.

[9] C. López and A. Ishizaka, "A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience," *Journal of Business Research*, vol. 103, pp. 495–507, Oct. 2019, https://doi.org/10.1016/j.jbusres.2017.09.050.

[10] A. Belhadi, S. Kamble, C. J. C. Jabbour, A. Gunasekaran, N. O. Ndubisi, and M. Venkatesh, "Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries," *Technological Forecasting and Social Change*, vol. 163, Feb. 2021, Art. no. 120447, https://doi.org/10.1016/j.techfore.2020.120447.

[11] H. Chesbrough, "Business Model Innovation: Opportunities and Barriers," *Long Range Planning*, vol. 43, no. 2–3, pp. 354–363, Apr. 2010, https://doi.org/10.1016/j.lrp.2009.07.010.

[12] P. Aversa, S. Haefliger, F. Hueller, and D. G. Reza, "Customer complementarity in the digital space: Exploring Amazon's business model diversification," *Long Range Planning*, vol. 54, no. 5, Oct. 2021, Art. no. 101985, https://doi.org/10.1016/j.lrp.2020.101985.

[13] S. Thammasang and S. Arunyanart, "Efficient Route Optimization for Ice Distribution: Enhanced VRPTW with Customer Retention Strategies," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 16346–16356, Oct. 2024, https://doi.org/10.48084/etasr.8239.

[14] H. H. Liu, L. C. Chang, C. W. Li, and C. H. Yang, "Particle Swarm Optimization-Based Support Vector Regression for Tourist Arrivals Forecasting," *Computational Intelligence and Neuroscience*, vol. 2018, pp. 1–13, Sep. 2018, https://doi.org/10.1155/2018/6076475.

[15] S. Sankhwar, D. Gupta, K. C. Ramya, S. Sheeba Rani, K. Shankar, and S. K. Lakshmanaprabu, "Improved grey wolf optimization-based feature subset selection with fuzzy neural classifier for financial crisis prediction," *Soft Computing*, vol. 24, no. 1, pp. 101–110, Jan. 2020, https://doi.org/10.1007/s00500-019-04323-6.

[16] D. Liu, Z. Deng, X. Mao, Y. Yang, and E. I. Kaisar, "Two-Echelon Vehicle-Routing Problem: Optimization of Autonomous Delivery Vehicle-Assisted E-Grocery Distribution," *IEEE Access*, vol. 8, pp. 108705–108719, 2020, https://doi.org/10.1109/ACCESS.2020.3001753.

[17] H. Xu, P. Pu, and F. Duan, "Dynamic Vehicle Routing Problems with Enhanced Ant Colony Optimization," *Discrete Dynamics in Nature and Society*, vol. 2018, pp. 1–13, 2018, https://doi.org/10.1155/2018/1295485.

[18] B. Ombuki, B. J. Ross, and F. Hanshar, "Multi-Objective Genetic Algorithms for Vehicle Routing Problem with Time Windows," *Applied Intelligence*, vol. 24, no. 1, pp. 17–30, Feb. 2006, https://doi.org/10.1007/s10489-006-6926-z.

[19] W. Ho, G. T. S. Ho, P. Ji, and H. C. W. Lau, "A hybrid genetic algorithm for the multi-depot vehicle routing problem," *Engineering Applications of Artificial Intelligence*, vol. 21, no. 4, pp. 548–557, Jun. 2008, https://doi.org/10.1016/j.engappai.2007.06.001.

[20] A. S. Bhagade and P. V. Puranik, "Artificial Bee Colony (ABC) Algorithm for Vehicle Routing Optimization Problem," *International Journal of Soft Computing and Engineering (IJSCE)*, vol. 2, no. 2, pp. 329–333, 2012.

[21] G. Fuellerer, K. F. Doerner, R. F. Hartl, and M. Iori, "Ant colony optimization for the two-dimensional loading vehicle routing problem," *Computers & Operations Research*, vol. 36, no. 3, pp. 655–673, Mar. 2009, https://doi.org/10.1016/j.cor.2007.10.021.

[22] J. Xu, F. Yan, and S. Li, "Vehicle routing optimization with soft time windows in a fuzzy random environment," *Transportation Research Part E: Logistics and Transportation Review*, vol. 47, no. 6, pp. 1075–1091, Nov. 2011, https://doi.org/10.1016/j.tre.2011.04.002.

[23] S. Karakatič and V. Podgorelec, "A survey of genetic algorithms for solving multi depot vehicle routing problem," *Applied Soft Computing*, vol. 27, pp. 519–532, Feb. 2015, https://doi.org/10.1016/j.asoc.2014.11.005.

[24] G. Gatica, G. Ahumada, J. W. Escobar, and R. Linfati, "Efficient Heuristic Algorithms for Location of Charging Stations in Electric Vehicle Routing Problems," *Studies in Informatics and Control*, vol. 27, no. 1, Mar. 2018, https://doi.org/10.24846/v27i1y201808.

[25] N. Dhanaraj, H. Nemlekar, S. Nikolaidis, and S. K. Gupta, "Proactive Contingency-Aware Task Allocation and Scheduling in Multi-Robot Multi-Human Cells via Hindsight Optimization," *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 13046–13060, 2025, https://doi.org/10.1109/TASE.2025.3546281.

[26] R. S. Sreerag and P. V. Shanmugam, "Vehicle routing model with backhauling for distribution of fresh vegetables among small retail channels: a case study in Kerala, India," *OPSEARCH*, Feb. 2025, https://doi.org/10.1007/s12597-025-00909-x.

[27] S. R. Kalluru, P. K. Reddy Gurijala, V. O. Reddy Puli, and L. R. Kalluru, "Bio-Inspired Advanced Warehouse System for Data Handling and Management," *Advanced Theory and Simulations*, Feb. 2025, Art. no. 2400980, https://doi.org/10.1002/adts.202400980.

[28] F. F. Rad, P. Oghazi, İ. Onur, and A. Kordestani, "Adoption of AI-based order picking in warehouse: benefits, challenges, and critical success factors," *Review of Managerial Science*, Feb. 2025, https://doi.org/10.1007/s11846-025-00858-1.

[29] D. C. Anaba, A. J. Kess-Momoh, and S. A. Ayodeji, "Optimizing supply chain and logistics management: A review of modern practices," *Open Access Research Journal of Science and Technology*, vol. 11, no. 2, pp. 020–028, 2024, https://doi.org/10.53022/oarjst.2024.11.2.0083.

[30] S. Inthasone, N. Pasquier, A. G. B. Tettamanzi, and C. Da Costa Pereira, "The BioKET Biodiversity Data Warehouse: Data and Knowledge Integration and Extraction," in *Advances in Intelligent Data Analysis XIII*, vol. 8819, H. Blockeel, M. Van Leeuwen, and V. Vinciotti, Eds. Springer International Publishing, 2014, pp. 131–142.

[31] M. S. Apriantoro, "Compliance of the Warehouse Receipt System with Maqasid al-Shari'ah Principles: Evidence from Indonesia," *Journal of International Law and Islamic Law*, vol. 20, pp. 150–162, 2024.

[32] A. K. H. Amar, M. A. Tahraoui, and A. Belmadani, "Solving Multi-Criteria Shortest Path by Optimization with Morphological Filters," *Engineering, Technology & Applied Science Research*, vol. 15, no. 1, pp. 19856–19864, Feb. 2025, https://doi.org/10.48084/etasr.9468.

[33] Y. Rahmani, W. Ramdane Cherif-Khettaf, and A. Oulamara, "The two-echelon multi-products location-routing problem with pickup and delivery: formulation and heuristic approaches," *International Journal of Production Research*, vol. 54, no. 4, pp. 999–1019, Feb. 2016, https://doi.org/10.1080/00207543.2015.1040127.

[34] C. L. Hwang, Y. J. Lai, and T. Y. Liu, "A new approach for multiple objective decision making," *Computers & Operations Research*, vol. 20, no. 8, pp. 889–899, Oct. 1993, https://doi.org/10.1016/0305-0548(93)90109-V.

[35] Y. Wei, Y. Wang, and X. Hu, "The two-echelon truck-unmanned ground vehicle routing problem with time-dependent travel times," *Transportation Research Part E: Logistics and Transportation Review*, vol. 194, Feb. 2025, Art. no. 103954, https://doi.org/10.1016/j.tre.2024.103954.

[36] J. Wu, Z. Yang, L. Zhen, W. Li, and Y. Ren, "Joint optimization of order picking and replenishment in robotic mobile fulfillment systems," *Transportation Research Part E: Logistics and Transportation Review*, vol. 194, Feb. 2025, Art. no. 103930, https://doi.org/10.1016/j.tre.2024.103930.

[37] M. Wang, X. Liu, L. Wang, Y. Bian, K. Fan, and R. Q. Zhang, "A data-driven optimization model for the scattered storage assignment with replenishment," *Computers & Industrial Engineering*, vol. 200, Feb. 2025, Art. no. 110766, https://doi.org/10.1016/j.cie.2024.110766.

[38] Y. Li, M. K. Lim, M. L. Tseng, W. Xiong, and Y. Shi, "An intelligent scheduling model for achieving green automotive outbound logistics," *Journal of Cleaner Production*, vol. 492, Feb. 2025, Art. no. 144874, https://doi.org/10.1016/j.jclepro.2025.144874.

[39] M. K. Osman, E. Mohamad, N. Kamarudin, and A. A. Rahman, "Warehouse operations optimisation through the implementation of lean methodology: A comprehensive review," *Multidisciplinary Reviews*, vol. 8, no. 4, Nov. 2024, Art. no. e2025110, https://doi.org/10.31893/multirev.2025110.

[40] T. Grzejszczak and W. Nocoń, "Cooperative and individual planning strategies for autonomous robots in warehouse parcel transportation," *Advances in Science and Technology Research Journal*, vol. 19, no. 1, pp. 406–418, Oct. 2024, https://doi.org/10.12913/22998624/195453.

[41] Q. Ma, L. Xu, L. Zhu, and P. Jia, "Research on storage location allocation in three-dimensional automated warehouse based on cargo damage control," *International Journal of Industrial Engineering Computations*, vol. 16, no. 1, pp. 177–196, 2025, https://doi.org/10.5267/j.ijiec.2024.10.003.

[42] X. Wang, L. Zhang, L. Wang, E. R. Zuñiga, X. V. Wang, and E. Flores-García, "Dynamic multi-tour order picking in an automotive-part warehouse based on attention-aware deep reinforcement learning," *Robotics and Computer-Integrated Manufacturing*, vol. 94, Aug. 2025, Art. no. 102959, https://doi.org/10.1016/j.rcim.2025.102959.

[43] K. Chen, T. Wang, H. Zhuo, and L. Cheng, "WGO: a similarly encoded whale-goshawk optimization algorithm for uncertain cloud manufacturing service composition," *Autonomous Intelligent Systems*, vol. 5, no. 1, Mar. 2025, Art. no. 7, https://doi.org/10.1007/s43684-025-00089-x.

[44] J. He, F. Wang, Y. Duan, Z. Yang, and J. Yang, "Energy-efficient train timetable optimization for tram system under multi-signal priority strategies," *Scientific Reports*, vol. 15, no. 1, Mar. 2025, Art. no. 8123, https://doi.org/10.1038/s41598-025-91891-3.

[45] C. Luo, Y. Hu, and F. Wang, "A big data approach to mitigating the MAUP in measuring excess commuting," *Computational Urban Science*, vol. 5, no. 1, Mar. 2025, Art. no. 14, https://doi.org/10.1007/s43762-025-00173-1.

[46] C. Chung, T. Ahn, S. W. Bae, and H. K. Ahn, "Parallel line centers with guaranteed separation," *Computational Geometry*, vol. 129, Dec. 2025, Art. no. 102185, https://doi.org/10.1016/j.comgeo.2025.102185.

[47] B. Granda and B. Vitoriano, "A Greedy Constructive Heuristic for Solving the Team Orienteering Problem with Variable Time Windows," *International Journal of Computational Intelligence Systems*, vol. 18, no. 1, Mar. 2025, Art. no. 69, https://doi.org/10.1007/s44196-025-00797-5.

[48] Q. Hu *et al.*, "Sustainable operational strategies for mixed fleets: Integrating autonomous and human-driven taxis with heterogeneous energy types," *Communications in Transportation Research*, vol. 5, Dec. 2025, Art. no. 100171, https://doi.org/10.1016/j.commtr.2025.100171.

[49] K. Kang and B. Q. Tan, "Multi-echelon reverse logistics network design in the context of circular economy: a Hong Kong case study," *Humanities and Social Sciences Communications*, vol. 12, no. 1, Jan. 2025, Art. no. 40, https://doi.org/10.1057/s41599-024-04323-4.

[50] J. Huang, "Minimizing makespan for mixed batch scheduling with identical machines and unequal ready times," *Scientific Reports*, vol. 15, no. 1, Feb. 2025, Art. no. 4924, https://doi.org/10.1038/s41598-025-89698-3.

[51] M. Qi, J. Chen, and Y. Yang, "Optimizing Fresh Warehouse Networks Using MIP and SARIMA Forecasting," in *Computing and Combinatorics*, vol. 15163, Y. Chen, X. Gao, X. Sun, and A. Zhang, Eds. Springer Nature Singapore, 2025, pp. 69–75.

[52] M. Karimi, "Inventory control of deteriorating items: A review," *International Journal of Industrial Engineering Computations*, vol. 16, no. 1, pp. 93–128, 2025, https://doi.org/10.5267/j.ijiec.2024.10.007.

[53] H. Li, D. Yu, Y. Zhang, and Y. Yuan, "A two-stage robust optimization model for emergency service facilities location-allocation problem under demand uncertainty and sustainable development," *Scientific Reports*, vol. 15, no. 1, Jan. 2025, Art. no. 2895, https://doi.org/10.1038/s41598-025-86129-1.

[54] F. Li *et al.*, "Simulation and optimization of cold chain logistics system towards lower carbon emission: a state-of-the-art review," *Carbon Research*, vol. 4, no. 1, Feb. 2025, Art. no. 22, https://doi.org/10.1007/s44246-024-00191-4.