Contents list avaliable at Directory of Open Access Journals (DOAJ)

JUTIN : Jurnal Teknik Industri Terintegrasi

Volume 8 Issue 4 2025, Page 4280-4291

ISSN: 2620-8962 (Online)

Journal Homepage: https://journal.universitaspahlawan.ac.id/index.php/jutin/index

Integrated Vehicle Routing and Cold Chain Optimization with Seasonal Variability Simulation for Fresh Fruit Distribution Networks

Thabed Tholib Baladraf✉

Department of Agroindustrial Technology, Faculty of Agricultural Technology, IPB University, Bogor

DOI: 10.31004/jutin.v8i4.50792

✉ Corresponding author:

[thabedtholib@apps.ipb.ac.id]

Article Info

Keywords:
Cold chain;
Distribution;
Fresh fruit;
Optimization route;
Seasonal variability

Abstract

Cold supply chains are critical for maintaining quality and quantity of fresh fruit commodities under seasonal variability, energy, and cost constraints. This study aims to (1) identify the most efficient vehicle routing algorithm to minimize fleet size and distance; (2) evaluate delivery performance through simulation under four scenarios (basic, adaptive, collaborative, technological); and (3) determine effective logistics risk management strategies. A spatial-variation heuristic was applied for routing, dynamic simulation for scenario analysis, and qualitative methods for risk strategies. Results show the sweep heuristic algorithm as most efficient, reducing shipping costs and distances by 33.02%, maximum travel time by 41.7%, and energy use by 29.49%. Scenario analysis identifies the technological scenario integrating AI, blockchain, and IoT as most optimal, ensuring cost-efficiency, truck utilization, fulfillment rate, minimal product loss, and flexibility. Recommended risk strategies include predictive systems, hybrid transportation, joint capacity investments, and adaptive refrigeration to strengthen cold chain resilience.

1. INTRODUCTION

The agricultural sector, particularly fresh fruit production, plays a vital role in food security, nutrition, and economic development across many regions worldwide. Fresh fruit commodities are highly perishable and therefore require a well-maintained cold supply chain to ensure quality and minimize post-harvest losses. Kirci et al. highlight that fresh fruits and vegetables contribute significantly to food loss because of their vulnerable characteristics (Kirci et al., 2022). To address this, cold chain infrastructure for fresh fruit distribution must operate within strict time windows and be closely monitored, especially in terms of environmental conditions. Temperature, humidity, and material handling are three critical factors that determine the quality of fresh fruit (Orjuela-Castro et al., 2022). However, the agricultural cold chain continues to face major logistical challenges, including low route efficiency, high cooling energy consumption, and frequent distribution delays. These challenges are further compounded by climate variability, fluctuating demand, and transportation resource constraints.

Received 11 September 2025; Received in revised form 18 September 2025 year; Accepted 30 September 2025

The complexity increases when distribution involves multiple cities or delivery points (Callejas-Molina et al., 2025; Thipparthy et al., 2024). In such cases, route planning becomes a crucial step to ensure that fruits reach consumers in good quality while maintaining industrial efficiency. Route planning that ignores the unique characteristics of fresh fruit commodities such as sensitivity to temperature, relative humidity, and seasonal supply demand variability can lead to increased spoilage, excessive energy use, and higher economic costs. Bancal and Ray report that losses of fruits and vegetables can reach 25–50% from the field to the consumer's table. This underscores the need for a comprehensive system that integrates vehicle route optimization with cold chain energy considerations and logistics risk management. Without such integration, fresh fruit distribution networks remain highly vulnerable to inefficiency and loss (Bancal & Ray, 2022).

Previous research on the vehicle routing problem (VRP) has primarily focused on optimizing travel distance or reducing fleet size (Fernando et al., 2024; Yadav et al., 2020). While some studies have addressed cold chain logistics through temperature control or cooling technologies, others have modeled seasonal variability or demand fluctuations in isolation (Baladraf & Marimin, 2025; Mustafa et al., 2024). o date, however, no study has holistically integrated vehicle routing, energy optimization, and scenario-based seasonal variability simulation in the context of fresh fruit supply chains. Moreover, few studies have examined logistics risk management strategies for this sector. This gap highlights the need for a more integrated and practical approach to fresh fruit cold chain optimization, with significant implications for the agroindustry.

To respond to this gap, the present study proposes an integrated model that combines vehicle route optimization, cold chain energy modeling, and seasonal variability simulation. The objectives are threefold: (1) to identify the most efficient routing methods in terms of fleet size and travel distance, (2) to evaluate delivery performance under different operational scenarios, and (3) to develop logistics risk management strategies specifically designed for the agricultural cold chain. The findings are expected to contribute to the development of smarter, more adaptive, and energy-efficient logistics systems. Ultimately, this can reduce food loss, minimize resource consumption, and enhance the overall efficiency of fresh fruit distribution networks.

2. METHODS

This research employed a quantitative approach that integrates VRP with spatial technology to determine optimal routes for interprovincial delivery of fresh fruit. The primary objective is to minimize delivery costs while maintaining product quality, with particular attention to the cooling energy required during transportation. To support this objective, a mathematical formulation was developed to define the sets, parameters, decision variables, and objective function of the model. This formulation serves as the analytical foundation for solving the VRP. By applying the model, the study seeks to identify optimal routes that balance transportation costs, energy consumption, and fleet utilization. The outcome is an efficient routing solution that ensures fresh fruit is delivered with minimal energy use and at the lowest possible cost.

2.1 Vehicle routing problem optimum route

Mathematical formulas play a crucial role in a modeling system because they are responsible for modeling real-world problems while taking into account various constraints so that they correspond to real-world conditions. Mathematical formulations consist of sets, parameters, decision variables, objective functions, and constraint functions must be defined at the outset and are presented below.

Set

i	:	Production center set
j	:	Destination city set
k	:	Refrigerated truck set
f	:	Fruit types set
t	:	Set of time periods

Parameter

D_{ift}	:	Demand for fruit f in city j period t
d_{ij}	:	Distance between center and destination city
C_{apk}	:	Refrigerated truck capacity k
FC_k	:	Fixed costs of truck use

VC	:	Variable cost per km
CC	:	Cooling cost per ton km
FC_{fuel}	:	Fuel consumption per km
P_{fuel}	:	Fuel price per liter

Decision Function

$x_{ijfkt} \geq 0$	:	Number of f fruits shipped
$y_{kt} \in \{0,1\}$	:	Decision on the use of trucks period t
$s_{ift} \geq 0$	:	Number of fruits f of center i stored in period t
$z_{ijkt} \in \{0,1\}$	:	Decision route
$x_{ijfkt} \geq 0$	:	Number of f fruits shipped

The components of the set, parameters, and decision variables that have been compiled are then used to compile the objective function and constraints as the final stage to measure the most optimal route. The objective function and constraint function are presented as follows.

Objective Function

$$\min Z = \sum_{t \in T} (C_{trans} + C_{cool} + C_{stor} + C_{loss}) \quad : \text{ Minimize costs}$$

$$C_{trans} = \sum_{k \in K} FC_k . y_{kt} + \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} VC . d_{ij} . z_{ijkt} + \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} FC_{fuel} . P_{fuel} . d_{ij} . z_{ijkt} \quad : \text{ Transportation costs}$$

$$C_{cool} = \sum_{i \in I} \sum_{j \in J} \sum_{f \in F} \sum_{k \in K} CC . x_{ijfkt} . d_{ij} \quad : \text{ Cooling costs}$$

$$C_{stor} = \sum_{i \in I} \sum_{f \in F} SC_f . s_{ift} \quad : \text{ Storage costs}$$

$$C_{loss} = \sum_{i \in I} \sum_{i \in J} \sum_{f \in F} \sum_{k \in K} PV_f . x_{ijfkt} . (1 - e^{-\delta_f . (\frac{d_{ij}}{v} + h_{ijt}}) \quad : \text{ Product loss costs}$$

Constraint Function

$$\sum_{i \in I} \sum_{k \in K} x_{ijfkt} \leq D_{ijft}, , \forall j \in J, f \in F, t \in T \quad : \text{ Destination city request}$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{f \in F} x_{ijfkt} \leq C_{apk} . y_{kt}, \forall k \in K, t \in T \quad : \text{ Truck capacity}$$

$$s_{ift} \leq S_{max}, \forall i \in I, f \in F, t \in T \quad : \text{ Storage capacity}$$

$$Q_{ijft}^{final} \geq Q_{min}, \forall i \in I, j \in J, f \in F, t \in T \quad : \text{ Minimum quality limits}$$

The mathematical formulations presented in the previous section provide the foundation for modeling the fresh fruit distribution problem. However, because obtaining exact solutions is computationally intensive, the problem is addressed using heuristic approaches to the VRP. The VRP framework is widely applied in distribution network design and is particularly relevant for perishable goods such as fresh fruit, where timely delivery and efficiency are critical. In this study, four heuristic algorithms are employed: Nearest Neighbor, Clarke and Wright Savings, Sweep, and Christofides. Each offers distinct working principles and advantages. The Nearest Neighbor algorithm applies the haversine formula to iteratively identify the closest demand location and construct routes. The Clarke and Wright Savings algorithm maximizes distance savings by merging routes, allowing a single vehicle to efficiently serve multiple cities (Mašek et al., 2024). The Sweep algorithm prioritizes deliveries within the same geographic zone, thereby reducing unnecessary cross-zone travel (Thammano & Rungwachira, 2021). Finally, the Christofides algorithm applies a greedy principle combined with minimum spanning tree and matching techniques, producing near-optimal routes that enable vehicles to serve multiple cities (Christofides et al., 1981; Tarantilis et al., 2005). To evaluate these algorithms, several parameters are considered, including transportation cost, total distance, fleet size, cooling time, and cooling energy load. The algorithm that produces the most efficient results will be used as a reference for recommending future fresh fruit delivery routes.

2.2 Dynamic simulation of seasonal variability

Dynamic simulation of seasonal variability in fresh fruit distribution networks is a powerful methodological tool. It is used to evaluate how different operational strategies affect supply chain performance, adaptability, and resilience. The simulation model developed in this study reflects the complexities and uncertainties of agribusiness logistics, particularly those arising from seasonal variations in production and consumption. To explore potential improvements, four distinct scenarios are formulated and analyzed in detail. The first is the base scenario, which represents current operational practices without major interventions and serves as a benchmark for comparison. The second is the adaptive scenario, which emphasizes strengthening internal capabilities such as inventory control, demand forecasting, and capacity flexibility to better manage fluctuations. The third is the collaborative scenario, which improves coordination and information sharing among farmers, processors, distributors, and retailers, thereby building a more integrated and responsive network. Finally, the technology-driven scenario incorporates digital tools—including the Internet of Things, big data analytics, and intelligent decision support systems—to enable real-time monitoring, predictive analysis, and automated responses.

The dynamic simulation covers a 36-month period to capture cyclical patterns, seasonal fluctuations, and long-term trends that shape the behavior of fresh fruit distribution systems. This extended horizon makes it possible to identify structural dynamics and recurring disruptions, particularly those caused by climate variability and changing consumer demand. As noted by Parker et al (Parker et al., 2015), system dynamics modeling helps reveal causal relationships, time delays, and feedback mechanisms within complex systems. This approach generates valuable strategic supports stakeholders in making more adaptive and data-driven decisions under uncertainty. The simulation relies on historical time-series data, especially production volumes and consumer demand patterns, as its primary input variables. These data are essential for representing dynamic interactions and behavioral responses within the system. To operationalize the model, two sub-components are integrated: a seasonal production model and a consumer demand model. Together, these sub-models provide a realistic representation of supply-demand dynamics, enhancing the reliability and policy relevance of simulation outcomes.

For each scenario, the simulation outputs include the dynamic allocation of distribution capacity, adjustments in transportation routes, inventory levels, and the degree of alignment between supply and demand over time. In addition, the model evaluates several key performance indicators, such as service level, stockout rates, delivery lead time, and overall logistics efficiency. To ensure transparency and replicability, the simulation is supported by a mathematical formulation consisting of system equations and decision variables. This quantitative framework provides a basis for analyzing trade-offs and optimizing supply chain strategies under uncertainty.

Parameters

$P_{(i,j,t,s)}$	:	Production of fruit center j month t year s (tons)
$P_{base(i,j)}$	:	Basic production of center i for fruit j (tons/month)
$A_{(j)}$	:	Seasonal variation amplitude of fruit j (0-1)
$\varphi_{(j)}$	:	Seasonal peak phase of fruit j (1-12)
t	:	Months of the year (1-12)
$e_{(t)}$	:	Error term
$Q_{(j,t)}$	:	Quality of fruit j in month t (0-100)
$Q_{base(j)}$	:	Basic quality of the fruit j
δ	:	Degradation factor
$d_{(t,\varphi(j))}$	:	Distance from peak season
$D_{(k,j,t,s)}$	:	Demand for city k, fruit j, month t, year s (tons)
$D_{base(k,j)}$	:	Basic demand of city k for fruit j (tons/month)
$F_{seasonal(j,t)}$	:	Seasonal factors of demand for fruit j in month t
$G_{(k,s)}$	:	Growth factor of city k in year s
$n_{(t)}$	:	Error term
$X_{(i,k,j,t,scenario)}$	:	Optimal allocation based on supply demand refers to the scenario
α	:	Efficiency factor

λ : Product loss factor
τ : Storage factor

Seasonal Production Model

$$F_{seasonal(j,t)} = \frac{A_{(j)}.Sin(2\pi(t-\varphi_{(j)})}{12}$$: Seasonal Function

$$Q_{(j,t)} = Q_{base(j)} - \delta.d_{(t,\varphi(j))}$$: Quality Model

Consumers Demand Model

$$D_{(k,j,t,s)} = D_{base(k,j)}.F_{seasonal(j,t)}.G_{(k,s)}.[1+n_{(t)}]$$: Demand Model

Based on the analysis of seasonal production patterns and consumer demand variability modeled previously, four different distribution scenarios were developed to evaluate how the distribution system can optimally bridge the gap between the seasonal supply of fresh fruit and consumer demand that varies spatially and temporally. Each scenario represents distinct levels of technological integration, coordination intensity, and decision-making autonomy in addressing the challenges of resource allocation and logistics efficiency among five major production centers. The parameters and operational assumptions defined for each scenario are systematically summarized and compared in Table 1 to support further evaluation and analysis.

Table 1. Dynamic Simulation Scenario Factors

Parameter	Base	Adaptive	Collaborative	Technology
α	1	0.85	0.75	0.70
λ	0.08	0.05	0.04	0.03
τ	3	2	1.5	1

Within the proposed analytical framework, a lower value for each evaluation metric indicates better performance. The dynamic simulation assesses four key metrics—cost per ton, demand fulfillment, product loss, and savings per ton—while incorporating stochastic variability to reflect real-world uncertainties. These indicators are used to compare the performance of four distribution scenarios (basic, adaptive, collaborative, and technological) and identify the most effective strategy for fresh fruit distribution. To ensure robustness and statistical confidence, the simulation is complemented by a Monte Carlo approach with 500 iterations. The best-performing scenario is further analyzed to derive managerial implications that support data-driven decision-making, improve logistics efficiency, minimize losses, and enhance responsiveness to seasonal and operational uncertainties.

2.3 Problem assumptions

Assumptions in this research are categorized into two main aspects, namely route optimization and dynamic simulation. In the route optimization design, several conditions are assumed to simplify and clearly define the problem. The research is carried out in West Java, which is identified as a major production area for fresh fruits. Five production centers are considered as part of the research design, with the following supply capacities: Bogor (20 tons), Cianjur (22 tons), Sukabumi (18 tons), Garut (24 tons), and Tasikmalaya (15 tons). On the distribution side, fresh fruit demand is represented at seven points: Jakarta (25 tons), Tangerang (8 tons), Bandung (15 tons), Semarang (12 tons), Surabaya (20 tons), Yogyakarta (10 tons), and Serang (7 tons). To ensure quality preservation, the fleet utilized consists of refrigerated trucks, each with a maximum capacity of 10 tons per unit. The distribution process is designed to be completed within 24 to 48 hours, while transportation costs are assumed at IDR 4,000 per kilometer. The commodities analyzed include five major fruits, namely apples, bananas, oranges, mangoes, and grapes, which represent both seasonal and non-seasonal variations. For the dynamic simulation, parameters such as peak harvesting season and production variability are incorporated to reflect realistic supply chain dynamics.

3. RESULT AND DISCUSSION

3.1 Vehicle routing problem optimum route

In the search for the optimal route, four algorithmic approaches were evaluated: Nearest Neighbor, Clarke and Wright savings, Sweep algorithm, and Christofides. The selection was based on several performance indicators relevant to the fresh fruit industry, including distribution cost, distance, number of vehicles, max delivery time, and energy consumption. Preliminary results show the Sweep method consistently outperforms the others, producing the lowest cost (IDR 24,608,440), the shortest travel distance (6,152.11 km), and the lowest energy consumption (128.48 kWh). Clarke and Wright also demonstrates competitive performance, while Nearest Neighbor produces the highest cost and longest distance traveled. Christofides achieves reasonable balance with fewer vehicles required but higher cost than Sweep. These findings highlight the trade-offs among the algorithms and suggest the Sweep method as the most promising option. The detailed results are presented in Table 2.

Table 2. Route Optimization Comparison Results

Algorithm	Cost (IDR)	Distance (Km)	Truck	Max Time (Hours)	Energy (Kwh)
Nearest Neighbor	36,737,960	9,184.49	15	40.1	182.22
Clarke & Wright	25,049,760	6,262.44	14	38	129.63
Sweep	24,608,440	6,152.11	15	23.4	128.48
Christofides	26,666,520	6,666.63	12	39.3	138.45

Beyond its descriptive advantages, the Sweep algorithm demonstrates consistent superiority over alternative heuristics due to its polar-angle clustering mechanism, which systematically produces non-overlapping and capacity-feasible routes. This geometric compactness not only reduces unnecessary cross-zone arcs the main contributors to extended travel time and higher refrigeration loads but also ensures a more balanced fleet utilization and less deadheading (Na et al., 2011). Such characteristics become particularly valuable under dynamic and seasonal demand fluctuations, where the Sweep algorithm allows rapid re-optimization, a capability that aligns well with Monte Carlo scenario analyses.

Empirically, these operational advantages translated into tangible performance gains in the present study. Cooling load calculations, which considered product, transmission, infiltration, and equipment loads and were normalized by a coefficient of performance (COP) of 1.5 following Calati et al. further confirmed the method's efficiency (Calati et al., 2022). As highlighted by Baladraf and Marimin, higher cooling requirements directly amplify environmental impacts; thus, the reduction achieved by Sweep signifies not only economic efficiency but also ecological benefits (Baladraf & Marimin, 2025). In comparison, Nearest Neighbor tends to generate myopic detours, Clarke & Wright often results in elongated merged routes requiring additional repairs, and Christofides adaptations incur post-split inefficiencies. By contrast, Sweep aligns more effectively with cold-chain key performance indicators, including shorter distance and time, lower refrigeration energy, improved service reliability, and enhanced product quality preservation. A detailed summary of the optimized refrigerated truck routes is presented in Table 3.

Table 3. Details of the Sweep Algorithm Recommended Route

Truck	Production Center	Destination City	Load (Ton)	Time Estimation (Hours)
1	Bogor	Jakarta	10	3.7
2	Bogor	Tangerang	8	4
3	Bogor	Serang	2	5.5
4	Cianjur	Jakarta	10	5
5	Cianjur	Serang	5	7.4
6	Sukabumi	Jakarta	5	5.2
7	Garut	Semarang	10	13.2
8	Garut	Surabaya	10	23.4
9	Garut	Yogyakarta	4	13.1
10	Tasikmalaya	Semarang	2	11.9
11	Tasikmalaya	Surabaya	10	22
12	Tasikmalaya	Yogyakarta	3	11.7
13	Cianjur	Bandung	7	4.1
14	Sukabumi	Bandung	8	5
15	Sukabumi	Yogyakarta	3	17.7
Total			97	153

Based on the route details presented above, it is identified that 15 trucks are assigned to fulfill delivery requests across multiple cities in different provinces. Each request directs the respective production center to dispatch fresh fruit according to the sweep algorithm principle, which organizes delivery routes by clustering destinations and sorting them in ascending order of polar angles. This approach ensures systematic routing, reduces travel distance, and enhances overall distribution efficiency across the designated supply network (Peya et al., 2019). In total, there is a demand for 97 tons of fresh fruits that need to be fulfilled, and it is estimated that this demand can be met within a maximum timeframe of 23.4 hours. The result of the recommended sweep algorithm routes presented in Figure 1.

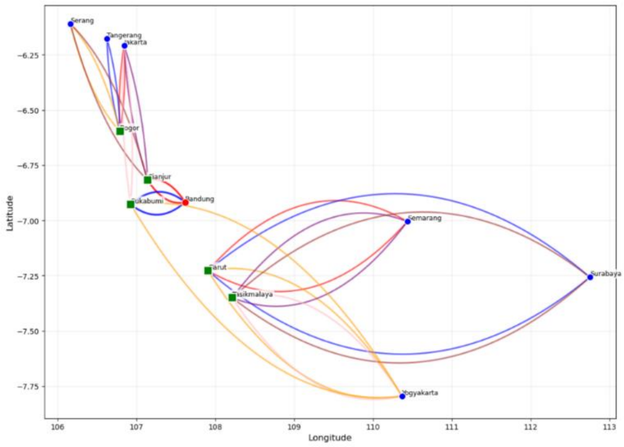


Fig 1. Sweep Algorithm Route Recommendations

3.2 Dynamic simulation of seasonal variability

A dynamic simulation addressing seasonal variability in fresh fruit distribution was conducted using a stochastic modeling approach across four distinct scenarios: base, adaptive, collaborative, and technology. Each scenario was designed to assess the system’s performance under varying degrees of supply uncertainty and management strategies. The stochastic model enabled the capture of random fluctuations associated with seasonal harvest patterns, providing insights into operational efficiency, fulfillment rates, and potential product losses. Preliminary findings highlight clear differences among the scenarios. The base case records the highest cost and lowest service level, while adaptive and collaborative approaches show progressive improvements in both efficiency and reliability. The technology-based scenario, however, stands out with the lowest operational cost, the highest fulfillment rate, and the smallest product loss, underscoring the potential of digital solutions in mitigating seasonal risks. A comprehensive summary of these results and comparative performance metrics is presented in Table 4.

Table 4. Results of Seasonal Variability Dynamic Simulation Comparison

Algorithm	Cost (IDR/ton)	Fulfillment (%)	Product Loss (%)	Savings (IDR)
Base	150,000	67.9	8	0
Adaptive	127,500	71.9	5	22,500
Collaborative	112,500	73.9	4	37,500
Technology	105,000	74.7	3	45,000

The favorable outcomes of the technology-based scenario are closely linked to the integration of advanced digital technologies, namely artificial intelligence (AI), the Internet of Things (IoT), and blockchain. AI supports predictive analytics, demand forecasting, and real-time optimization of routing, scheduling, and inventory management, which collectively enhance decision-making and system responsiveness under variable supply conditions. IoT enables continuous and end-to-end monitoring of critical environmental parameters such as temperature and humidity, thereby ensuring product quality and reducing spoilage risks during transit. Blockchain further strengthens supply chain governance by providing secure, tamper-resistant records that improve traceability, transparency, and accountability across stakeholders. Taken together, the synergistic application of these technologies, as demonstrated in the simulation results, reduces operational inefficiencies and uncertainty while achieving measurable improvements in service levels, resource utilization, and overall distribution performance under dynamic and uncertain seasonal conditions.

Despite its advantages, implementing a technology-intensive strategy remains challenging. The primary barriers include the substantial initial capital required and the development of robust digital infrastructure, which are often beyond the reach of many stakeholders. These constraints are particularly evident among small- and medium-scale agroindustrial enterprises, where financial limitations and limited access to advanced digital resources hinder widespread adoption. Yigezu et al. note that high upfront costs and the demand for digitally skilled labor are critical barriers to the adoption of advanced technologies in agriculture. Furthermore, the dynamic simulation within the proposed modeling framework relies on a stochastic approach. While effective in capturing probabilistic variability, such models have inherent limitations in representing nonlinear system behaviors and rare disruptive events (Yigezu et al., 2018). As noted by Marsh et al., emphasize, stochastic models may lack the flexibility required to fully capture dynamic uncertainties in real-world conditions (Marsh et al., 2025). To address this limitation, a Monte Carlo simulation is incorporated. This approach applies random sampling from defined probability distributions to simulate a wide range of potential outcomes. By doing so, it enhances the robustness of the analysis and allows for a probabilistic exploration of uncertainty and variability (Newell & and Sanders, 2015). The results of the Monte Carlo simulation are presented in Figure 2 and Figure 3, providing additional insights into the resilience of the distribution system under uncertain conditions.

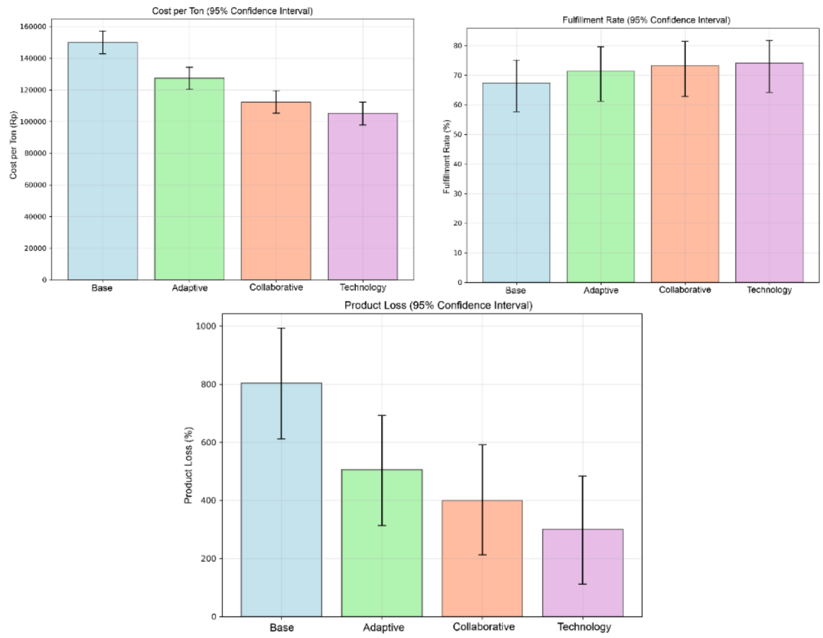
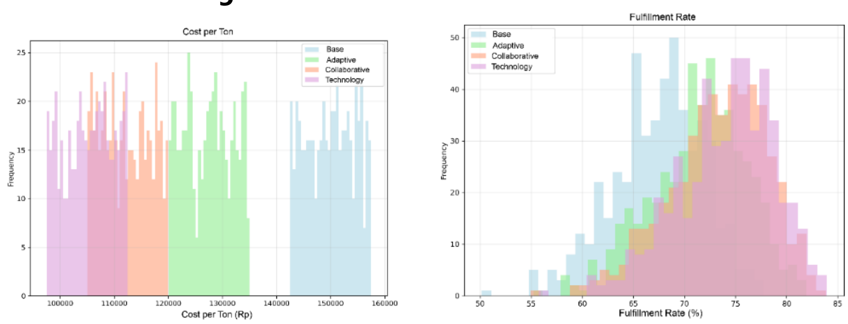


Fig 2. Monte Carlo Simulation Result



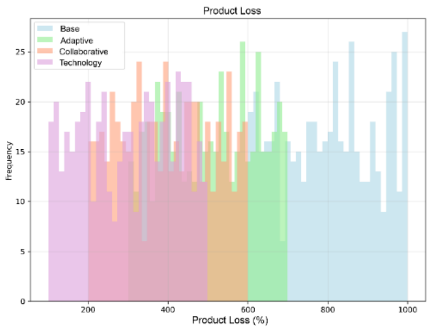


Fig 3. Monte Carlo Simulation Distribution Results

3.3 Managerial implications

Based on the results of a simulation of fresh fruit distribution using four main scenarios: baseline, adaptive, collaborative, and technology which consider harvest season variability as the primary source of supply uncertainty, a number of strategic recommendations for logistics risk management in the agroindustry context were obtained. These recommendations include: (1) mitigating risks associated with supply variability, (2) enhancing the flexibility of transportation capacity, (3) implementing a collaborative risk management model, and (4) adopting adaptive and real-time cooling technology. In terms of mitigating supply variability risks, an initial step that can be taken is the implementation of an early warning system based on predictive models. This model enables management to identify potential disruptions caused by seasonal fluctuations and proactively anticipate them. This strategy aligns with an adaptive approach proven to enhance supply chain responsiveness, as demonstrated in simulation results. Additionally, geographical diversification strategies, such as multisourcing, are recommended to reduce the risk of supply shocks caused by reliance on a single production region. This diversification creates alternative supply reserves and strengthens logistics resilience. The provision of dynamic buffer stocks adjusted to seasonal patterns is also capable of improving fulfillment rates (Jeong & Choi, 2023).

Transportation capacity flexibility is a key element in optimizing distribution. This is because the majority of transportation used is still of a single type, which sometimes leads to waste that impacts efficiency. Management may consider implementing a hybrid fleet composition, combining various types of vehicles with different capacities and efficiencies. This approach not only reduces transportation costs but also allows flexibility in handling spikes or drops in shipment volumes. Additionally, multi-echelon and cross-docking strategies can be applied to improve vehicle utilization and reduce travel distances, thereby enhancing overall logistics efficiency (Benrqya, 2019).

Collaborative risk management is also an increasingly relevant approach in the context of the agro-industrial supply chain. The collaborative risk management model allows stakeholders to share resources and risks more fairly. One concrete strategy in this regard is joint capacity investment, which involves collective investment in logistics infrastructure such as cold storage facilities, temperature monitoring systems, or refrigerated truck fleets (Wang & Shao, 2021). Such collaborative investments not only enhance efficiency and synergy among businesses but also accelerate the payback period. The final recommendation is the procurement of adaptive cooling technology equipped with real-time monitoring systems, which is crucial for maintaining the quality of fresh products during the distribution process. This technology enables continuous temperature monitoring, early detection of deviations in storage conditions, and prediction of potential product damage. As a result, this technology contributes to minimizing waste, both in terms of logistics costs and product losses due to undetected damage. Adaptive cooling technology has proven effective in maintaining product quality and extending shelf life, which are critical factors in the distribution of perishable agricultural products.

4. CONCLUSION

This study demonstrates that integrating cold chain route optimization with advanced simulation techniques provides a robust solution for fresh fruit distribution under seasonal variability. Among the tested vehicle routing algorithms, the sweep algorithm yielded the most efficient performance in terms of cost, distance, delivery time, and energy consumption, thereby addressing the critical industry need for reliability in time-sensitive logistics. Beyond algorithmic efficiency, the incorporation of dynamic stochastic simulation and Monte Carlo analysis confirmed that a technology-intensive strategy represents the most resilient option when faced with uncertain supply and demand patterns. The novelty of this research lies in bridging classical vehicle routing optimization with modern digital technologies, offering a dual perspective that enhances both operational performance and supply chain resilience. From a managerial standpoint, the study highlights four actionable strategies: predictive early warning systems, flexible hybrid transportation capacity, collaborative risk management, and adaptive cooling technologies with real-time monitoring. These findings provide practical guidance for industry stakeholders seeking to enhance sustainability and competitiveness in agri-food supply chains. Future research should expand this framework across broader geographical contexts and explore integration with real-time market data, further strengthening decision-making under uncertainty and advancing the digitalization of perishable food logistics.

5. ACKNOWLEDGMENTS

The authors gratefully acknowledge the PMDSU scholarship support from the Ministry of Education, Culture, Research and Technology Indonesia and IPB University. The author also acknowledges Prof. Dr. Ir. Marimin, M.Sc. for his guidance and direction in conducting the research

6. REFERENCES

Baladraf, T. T., & Marimin. (2025). Food Cold Chain Sustainability and Resiliency: Bibliometric Analysis and Emerging Trends. *BIO Web of Conferences*, *167*. https://doi.org/10.1051/bioconf/202516701004

Bancal, V., & Ray, R. C. (2022). Overview of Food Loss and Waste in Fruits and Vegetables: From Issue to Resources. In R. C. Ray (Ed.), *Fruits and Vegetable Wastes* (pp. 3–29). Springer Nature Singapore. https://doi.org/10.1007/978-981-16-9527-8_1

Benrqya, Y. (2019). Costs and benefits of using cross-docking in the retail supply chain. *International Journal of Retail & Distribution Management*, *47*(4), 412–432. https://doi.org/10.1108/IJRDM-07-2018-0119

Calati, M., Zilio, C., Righetti, G., Longo, G. A., Hooman, K., & Mancin, S. (2022). Latent thermal energy storage for refrigerated trucks. *International Journal of Refrigeration*, *136*, 124–133. https://doi.org/10.1016/j.ijrefrig.2022.01.018

Callejas-Molina, R. A., Vazquez-Leal, H., Huerta-Chua, J., Filobello-Nino, U. A., Sandoval-Hernandez, M. A., Aguilar-Velazquez, R., & Diaz-Carmona, J. (2025). Circuit Analysis Approach for Sustainable Routing Optimization with Multiple Delivery Points. *Sustainability* 17(7). https://doi.org/10.3390/su17072866

Christofides, N., Mingozzi, A., & Toth, P. (1981). Exact algorithms for the vehicle routing problem, based on spanning tree and shortest path relaxations. *Mathematical Programming*, *20*(1), 255–282. https://doi.org/10.1007/BF01589353

Fernando, W. M., Thibbotuwawa, A., Perera, H. N., Nielsen, P., & Kilic, D. K. (2024). An integrated vehicle routing model to optimize agricultural products distribution in retail chains. *Cleaner Logistics and Supply Chain*, *10*, 100137. https://doi.org/10.1016/j.clscn.2023.100137

Jeong, H., & Choi, C. (2023). Adaptive Supply Chain System Design for Fruit Crops under Climate Change. *Systems*, 11(10). https://doi.org/10.3390/systems11100514

Kirci, M., Isaksson, O., & Seifert, R. (2022). Managing Perishability in the Fruit and Vegetable Supply Chains. *Sustainability*, 14(9). https://doi.org/10.3390/su14095378

Marsh, E., Hattam, L., & Allen, S. (2025). Stochastic error propagation with independent probability distributions in LCA does not preserve mass balances and leads to unusable product compositions—a first quantification. *The International Journal of Life Cycle Assessment*, *30*(2). https://doi.org/10.1007/s11367-024-02380-0

Mašek, J., Pálková, A., & Bulková, Z. (2024). Application of the Clark–Wright Method to Improve the Sustainability of the Logistic Chain. *Applied Sciences* 14(21). https://doi.org/10.3390/app14219908

Mustafa, M. F. M. S., Navaranjan, N., & Demirovic, A. (2024). Food cold chain logistics and management: A review of current development and emerging trends. *Journal of Agriculture and Food Research*, *18*, 101343. https://doi.org/10.1016/j.jafr.2024.101343

Na, B., Jun, Y., & Kim, B.-I. (2011). Some extensions to the sweep algorithm. *The International Journal of Advanced Manufacturing Technology*, *56*(9), 1057–1067. https://doi.org/10.1007/s00170-011-3240-7

Newell, Q., & and Sanders, C. (2015). Stochastic Uncertainty Propagation in Monte Carlo Depletion Calculations. *Nuclear Science and Engineering*, *179*(3), 253–263. https://doi.org/10.13182/NSE13-44

Orjuela-Castro, J. A., Orejuela-Cabrera, J. P., & Adarme-Jaimes, W. (2022). Multi-objective model for perishable food logistics networks design considering availability and access. *Opsearch*, *59*(4), 1244–1270.

https://doi.org/10.1007/s12597-022-00594-0

Parker, A. M., Srinivasan, S. V, Lempert, R. J., & Berry, S. H. (2015). Evaluating simulation-derived scenarios for effective decision support. *Technological Forecasting and Social Change*, *91*, 64–77. https://doi.org/10.1016/j.techfore.2014.01.010

Peya, Z. J., Akhand, M. A. H., Sultana, T., & Hafizur Rahman, M. M. (2019). Distance based Sweep Nearest algorithm to solve Capacitated Vehicle Routing Problem. *International Journal of Advanced Computer Science and Applications*, *10*(10), 259–264. https://doi.org/10.14569/ijacsa.2019.0101036

Tarantilis, C. D., Ioannou, G., & Prastacos, G. (2005). Advanced vehicle routing algorithms for complex operations management problems. *Journal of Food Engineering*, *70*(3), 455–471. https://doi.org/10.1016/j.jfoodeng.2004.09.023

Thammano, A., & Rungwachira, P. (2021). Hybrid modified ant system with sweep algorithm and path relinking for the capacitated vehicle routing problem. *Heliyon*, *7*(9), e08029. https://doi.org/10.1016/j.heliyon.2021.e08029

Thipparthy, K. R., Khalaf, M. I., Yogi, K. S., Alghayadh, F. Y., Yusupov, A., Maguluri, L. P., & Ofori-Amanfo, P. (2024). Optimizing delivery routes for sustainable food delivery for multiple food items per order. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00326-y

Wang, J., & Shao, W. (2021). Joint Capacity Investment, Collecting and Pricing Decisions in a Capacity Constraint Closed-Loop Supply Chain Considering Cooperation. In *Sustainability* (Vol. 13, Issue 16). https://doi.org/10.3390/su13168725

Yadav, R. K., Kishor, G., Himanshu, & Kashyap, K. (2020). Comparative Analysis of Route Planning Algorithms on Road Networks. *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, 401–406. https://doi.org/10.1109/ICCES48766.2020.9137965

Yigezu, Y. A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., & Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006