OPTIMIZATION OF MULTI-ECHELON DISTRIBUTION SYSTEM WITH TIME WINDOW USING EVOLUTIONARY ALGORITHM

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Name : Muhammad Hoqqil Fatwa
Student Number : 19522214

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FACULTY OF INDUSTRIAL TECHNOLOGY

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SEPULUH RIBU RUPIAH

Muhammad Hoqqil Fatwa
19522214

UNIVERSITAS
ISLAM
INDONESIA

FAKULTAS
TEKNOLOGI INDUSTRI

Gedung KH. Mas Mansur
Kampus Terpadu Universitas Islam Indonesia
Jl. Kaliurang km 14,5 Yogyakarta 55584
T. (0274) 898444 ext. 4100, 4101
F. (0274) 895007
E. fti@uii.ac.id
W. fti.uii.ac.id

RESEARCH COMPLETION LETTER

Nomor: 01/Ka.Lab.Delsim/70/Lab.DELSIM/II/2026

Assalamu'alaikum Warahmatullahi Wabarakatuh

Kami yang bertanda tangan dibawah ini, menerangkan bahwa mahasiswa dengan keterangan sebagai berikut :

Nama	:	Muhammad Hoqqil Fatwa
No. Mhs	:	19522214
Dosen Pembimbing	:	Ir. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., IPM.

Telah selesai melaksanakan penelitian yang berjudul "OPTIMIZATION MULTI-ECHELON DISTRIBUTION SYSTEM WITH TIME WINDOW USING EVOLUTIONARY ALGORITHM" di Laboratorium Pemodelan dan Simulasi Industri (DELSIM) Program Studi Teknik Industri, Fakultas Teknologi Industri, Universitas Islam Indonesia tercatat mulai tanggal 1 Desember 2025 sampai dengan tanggal 1 Februari 2026.

Demikian surat keterangan kami keluarkan, agar dapat dipergunakan sebagaimana mestinya.

Wassalamu'alaikum Warahmatullahi Wabarakatuh

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Mengetahui,
Kepala Lab. Pemodelan dan Simulasi Industri

Didin Dwi Novianto, S.T., M.LSCM.

SUPERVISOR APPROVAL SHEET

OPTIMIZATION OF MULTI-ECHELON DISTRIBUTION SYSTEM WITH TIME WINDOW USING EVOLUTIONARY ALGORITHM

Yogyakarta, February 02, 2026

Supervisor,

(Ir. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., IPM.)

EXAMINERS' APPROVAL PAGE

OPTIMIZATION OF MULTI-ECHELON DISTRIBUTION SYSTEM WITH TIME WINDOW USING EVOLUTIONARY ALGORITHM

UNDERGRADUATE THESIS

Written by:

Name	: Muhammad Hoqqil Fatwa
Student Number	: 19522214

Has been defended before the board of examiners in partial fulfillment of the requirement for Bachelor Degree in Industrial Engineering at the Faculty of Industrial Technology, Universitas Islam Indonesia

Yogyakarta, *February 11, 2026*

Board of Examiners

Ir. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., IPM.
Chairman

Dr. Harwati, S.T., M.T.
Member I

Dr. Agus Mansur, S.T., M.Eng.Sc.
Member II

Acknowledged by,
Head of Undergraduate Program in Industrial Engineering
Faculty of Industrial Technology
Universitas Islam Indonesia

Ir. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., IPM.
015220101

DEDICATION PAGE

Alhamdulillahirabbil'alamin

All praise and gratitude be to Allah SWT, the Most Gracious and the Most Merciful. It is only by His grace, guidance, and blessings that I was able to complete this undergraduate thesis entitled "Optimization of Multi-Echelon Distribution System with Time Window Using Evolutionary Algorithm."

I dedicate this humble work to the people who have been my greatest strength:

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May this thesis provide benefits to those who read it and become a charity (*Jariyah*) for me in the future.

MOTTO

Wa an laysa lil-insani illa ma sa'a
"And that there is not for man except that (good) for which he strives."
(Q.S. An-Najm: 39)

PREFACE

Bismillahirrahmanirrahim

All praise and profound gratitude are dedicated to Allah SWT, whose infinite grace, mercy, and divine will have empowered the author to successfully finalize this undergraduate thesis entitled, "Optimization of a Multi-Echelon Distribution System with Time Windows Using an Evolutionary Algorithm." Furthermore, abundant salawat and heartfelt peace are conveyed to the Prophet Muhammad SAW, the revered messenger who has guided humanity from the depths of ignorance into the luminous realm of profound knowledge and unwavering faith.

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The author acknowledges the limitations of this thesis and welcomes constructive feedback. It is hoped that this research will benefit future scholars and contribute meaningfully to the advancement of distribution optimization strategies.

Yogyakarta, February 2, 2026

Muhammad Hoqqil Fatwa

ABSRTACT

Distribution efficiency plays a critical role in modern supply chain management, particularly when facing strict delivery schedules and high operational costs. This research addresses the optimization of a multi-echelon distribution system for a logistics company, PT. POS INDONESIA, which currently faces challenges in route planning and fleet utilization across its network of 1 main warehouse, 9 overflow warehouses, and 40 retailers. The complexity of the problem is compounded by the presence of strict Time Window constraints, where failure to deliver within specified hours results in service level violations.

This study proposes a mathematical model for the Multi-Echelon Distribution System with Time Windows and utilizes an Evolutionary Algorithm to solve it. The algorithm was implemented to minimize total travel distance while strictly adhering to vehicle capacity and customer service time limits. The optimization process involved replacing the traditional "nearest-neighbor" manual planning approach with a global search heuristic capable of generating efficient route clusters.

The results demonstrate significant improvements in system performance. The implementation of the Evolutionary Algorithm reduced the total travel distance by 33.3%, decreasing from 255.8 km in the baseline scenario to 170.5 km in the optimized model. Furthermore, the optimized routing strategy allowed for a 25% reduction in the required fleet size, lowering the number of active vehicles from 12 to 9 units. Most importantly, the model achieved a 100% service level by eliminating all time window violations, compared to 12 violations observed in the baseline schedule. These findings confirm that Evolutionary Algorithms are highly effective tools for solving complex logistics problems, providing tangible benefits in terms of cost reduction and operational reliability.

Keywords: Multi-Echelon Distribution, Time Window, Evolutionary Algorithm, Logistics Optimization.

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CHAPTER 1

INTRODUCTION

1.1 Research Background

In recent years, the complexity of global supply chains has increased significantly, prompting companies to optimize their distribution systems in order to meet customer demands more quickly, efficiently, and reliably. Multi-echelon distribution systems are a crucial component of modern supply chains, involving several levels such as manufacturers, distribution centers, and retailers. Multi-echelon distribution systems are a crucial component of modern supply chains, involving several levels such as manufacturers, distribution centers, and retailers. These systems are designed to ensure that goods are delivered to customers at minimal cost and within optimal lead times (Simchi-Levi et al., 2022). However, as supply chains grow in scale and complexity, managing them becomes increasingly challenging—especially when delivery operations must comply with time window constraints, which are strict time limits within which deliveries must be made to meet service level agreements (Chen et al., 2020).

In Indonesia, distribution systems face persistent challenges due to geographical complexity, uneven infrastructure development, and the archipelagic nature of the country, which often leads to high logistics costs and delays in delivery performance (World Bank, 2021). These issues highlight the critical need for more efficient and intelligent distribution planning. Indonesia’s distribution system remains one of the most inefficient in Southeast Asia, contributing to high logistics costs estimated at around 23% of GDP, far above the global average of 11% (World Bank, 2021; Indonesia Logistics Association, 2022). The country’s archipelagic geography, combined with underdeveloped transport infrastructure and poor coordination between supply chain actors, leads to long lead times, delivery unreliability, and regional service gaps. These inefficiencies hinder the competitiveness of many industries, particularly warehousing and retail distribution sectors, which rely heavily on timely and cost-effective delivery networks.

The presence of time windows further increases the difficulty of distribution planning, requiring companies to coordinate not only the volume and route of shipments but also the precise timing of deliveries. Failure to meet time windows can result in penalties, increased costs, or reduced customer satisfaction. As a result, optimizing distribution operations under such constraints has become a critical objective for businesses, particularly those involved in fast-moving consumer goods, retail, and e-commerce (Liu et al., 2023).

The rising cost of fuel, labor, and overall logistics operations has intensified the pressure on companies to achieve greater efficiency in their distribution networks. Global events, geopolitical tensions, and inflationary pressures have contributed to significant volatility in energy markets, directly impacting transportation expenses (International Energy Agency, 2023). Moreover, increasing labor costs for drivers and warehouse personnel, alongside stringent regulatory requirements, further drive up the total cost of goods movement (Ghahramani et al., 2021). For businesses operating in a complex geographical landscape like Indonesia, these cost pressures are particularly acute, making optimized route planning and resource allocation not just a matter of competitive advantage, but often one of economic survival. Therefore, developing robust optimization models is essential for mitigating these financial burdens and ensuring sustainable logistics operations.

Many previous studies have used traditional optimization approaches such as Mixed-Integer Linear Programming (MILP) to model distribution systems. While MILP offers strong mathematical rigor, it tends to struggle when applied to large-scale or highly constrained problems due to long computation times and sensitivity to problem size (Fahimnia et al., 2015 In such scenarios, heuristic and metaheuristic approaches offer more practical alternatives. One such approach is the Evolutionary Algorithm**.** Their ability to effectively explore vast solution spaces, find high-quality (near-optimal) solutions in acceptable computational time, and their inherent robustness to problem complexity makes them particularly well-suited for the dynamic and large-scale distribution challenges faced by companies like PT. POS INDONESIA (Gendreau et al., 2008; Mirjalili, 2019). This pragmatic advantage allows for the development of deployable solutions, even when exact optimality is elusive due to problem size and complexity.

This study applies the Evolutionary Algorithms to optimize the multi-echelon distribution system of a warehousing company that manages product deliveries to numerous retail clients across different geographic locations. The company faces difficulties in planning cost-effective distribution routes while adhering to the time windows demanded by each client. Applying Evolutionary Algorithms in this context allows the development of a solution that simultaneously minimizes logistics costs and ensures service-level requirements are met. Unlike traditional methods, Evolutionary Algorithms is more adaptive and capable of providing near-optimal solutions in a reasonable amount of time, even in dynamic and uncertain environments (Mirjalili, 2019).

Furthermore, the application of Evolutionary Algorithms in real-world logistics problems continues to grow, demonstrating its relevance and practicality. Several studies have shown that Evolutionary Algorithms can outperform classical approaches in terms of flexibility, scalability, and robustness, especially for vehicle routing and scheduling problems under time constraints (Prins et al., 2014; Lin et al., 2014).

By using the Evolutionary Algorithms, this research aims to deliver a comprehensive and efficient solution to optimize the company’s distribution network. It not only contributes to the operational efficiency of the company but also enhances the academic understanding of metaheuristic applications in supply chain and logistics management. The study is expected to serve as a practical reference for both practitioners and future researchers dealing with distribution optimization under realistic constraints.

1.2 Problem Formulation

From the explanation of the background above, so the problems that can be raised in this research are:

1. How can the distribution process in a multi-echelon warehousing system be optimized to minimize logistics costs while satisfying delivery time windows?
2. How effective is the implementation of an Evolutionary Algorithms to improve

the distribution system?

1.3 Research Objectives

Based on the problem formulation above, the following are the objectives of this research:

1. To develop an optimization model for the multi-echelon distribution system using Evolutionary Algorithms implemented.
2. To evaluate the effectiveness of the Evolutionary Algorithms model in minimizing distribution costs and improving delivery performance.

1.4 Research Benefits

The benefits that can be expected from doing this research are as follows:

1. For the Company

   This research provides the warehousing company with an effective optimization approach using Evolutionary Algorithms to improve its multi-echelon distribution performance. The results can help minimize total distribution costs and improve delivery reliability within specified time windows, enhancing customer satisfaction and operational efficiency.
2. For Researchers

   This study contributes to the body of knowledge in supply chain optimization by demonstrating how Evolutionary Algorithms can be applied to complex multi-echelon distribution systems with time window constraints, offering an alternative to traditional mathematical methods like MILP
3. For Further Researchers

   This research can serve as a reference for future studies that aim to solve real-world distribution problems using intelligent algorithms. The use of Evolutionary Algorithms as a simulation and optimization tool may also guide further development and comparison with other metaheuristic techniques such as Particle Swarm Optimization or Ant Colony Optimization.

1.5 Scope of Problem

Establishing clear research boundaries is essential to maintain focus and prevent the study from deviating from its core objectives. Therefore, the primary limitations guiding this research are outlined as follows:

1. This research was conducted on PT. POS INDONESIA
2. Several assumptions are made to simplify the problem, such as deterministic demand, fixed transportation capacity, and static time windows. In reality, demand and delivery conditions may vary dynamically.
3. The performance of the Evolutionary Algorithms depends on specific parameter tuning (such as population size, crossover rate, mutation rate). This study uses standard settings, which may not necessarily yield the global optimum for all instances.
4. The model is developed and solved using Evolutionary Algorithms
5. The optimization is based on the available data provided by the company. Any inaccuracy or incompleteness in the data may affect the quality of the solution generated by the model.

1.6 Systematical Writing

The systematical writing in this thesis is organized as follows:

CHAPTER I	**INTRODUCTION**
	This chapter presents the background of the study, identifies the core problems, and defines the research objectives and scope. It also outlines the significance of the research and provides an overview of the thesis structure.
CHAPTER II	**LITERATURE REVIEW**
	This section explores existing theories and previous studies related to multi-echelon distribution systems and evolutionary algorithms. It establishes the theoretical framework and identifies the research gap.

CHAPTER III **RESEARCH METHODOLOGY**

This chapter details the systematic approach used to conduct the study, including data collection methods, model formulation, and the steps involved in implementing the evolutionary algorithm.

CHAPTER IV **DATA COLLECTION AND PROCESSING**

This chapter focuses on the presentation of gathered data and the computational steps taken to optimize the distribution system based on the defined time windows.

CHAPTER V **DISCUSSION**

A comprehensive analysis of the results is provided here, comparing the outcomes of the optimization against the research objectives and interpreting the findings.

CHAPTER VI **CONCLUSION**

The final chapter summarizes the research findings, offers answers to the problem statements, and suggests potential areas for future study.

CHAPTER II

LITERATURE REVIEW

2.1 Literature Review

Awwalu, H. B., Abdullahi, N., & Hussaini, M. (2023) proposes a conceptual Mixed-Integer Linear Programming (MILP) model for multi-objective optimization of water distribution systems (WDS), aiming to minimize design and operational costs and maximize reliability, which is relevant to multi-echelon distribution systems that also seek cost efficiency and reliable service. The model considers three objective functions: minimizing pipeline, pump, and fuel costs; maximizing the reliability of water production; and minimizing water head loss and leakage. These objectives are subject to constraints such as mass and energy conservation, minimum nodal pressure, available pipe sizes, and flow requirements. While the paper specifically addresses WDS, its focus on multi-objective optimization and the use of Differential Evolution (DE) as a metaheuristic algorithm for solving complex, constrained problems has direct applicability to multi-echelon distribution systems. The DE algorithm's strengths, including its simple structure, robustness, and ability to handle real-valued variables, make it a suitable choice for optimizing such systems, even though the specific "time window" constraint often found in logistics distribution is not explicitly modeled as a separate objective or constraint in this water distribution context. The verification and validation processes, comparing MATLAB outputs with empirical results, confirm the model's effectiveness in achieving optimal solutions for conflicting objectives.

DERSE, O., & GÖÇMEN, E. (2023) proposes a two-stage optimization approach for a biogas supply chain, which can be analogously applied to multi-echelon distribution systems, focusing on facility location and distribution planning. The first stage utilizes a goal programming approach to identify optimal biogas plant locations by minimizing costs and maximizing biogas energy potential. The second stage, which is directly relevant to distribution system optimization, employs a Mixed-Integer Linear Programming (MILP) approach to determine the optimal locations for biogas vehicle charging stations (BVS), considering factors like population density, capacity, and cost. The objective function for this stage minimizes transportation and BVS installation costs while maximizing profit from vehicle density. Although the research does not explicitly include "time window" constraints, its multi-objective optimization framework and the use of metaheuristic-like MILP and Goal Programming for location and distribution decisions in a supply chain context offer valuable insights for designing efficient multi-echelon distribution networks, particularly in addressing cost-effectiveness and capacity allocation across different echelons. The study's sensitivity analysis further demonstrates how changes in demand coverage rates influence optimal facility location and capacity, a critical consideration in dynamic distribution environments.

Wang, Z., & Wen, P. (2020) addresses the optimization of a low-carbon, two-echelon heterogeneous-fleet vehicle routing problem (LC-2EHVRP) for cold chain logistics, incorporating mixed time windows and customer satisfaction, which is highly relevant to multi-echelon distribution systems with time window constraints. The proposed model minimizes economic costs and carbon emissions while maximizing customer satisfaction, a multi-objective approach critical for complex distribution networks. It integrates a mixed time window with a penalty mechanism to precisely measure customer satisfaction, moving beyond traditional hard or soft time window constraints. To solve this NP-hard problem, an Adaptive Evolutionary Algorithms (AEA) is developed and validated through benchmark tests, demonstrating its superior performance compared to a classic Evolutionary Algorithms (EA). The study's real cold chain case study reveals a trade-off between customer satisfaction, economic costs, and environmental protection, emphasizing that modest carbon pricing policies have limited impact on emission control unless carbon prices are significantly high. The findings offer managerial implications for balancing these conflicting objectives in cold chain logistics, suggesting that appropriate external time window settings can simultaneously reduce carbon emissions and enhance customer satisfaction in multi-echelon distribution systems.

Sbai, N., & Berrado, A. (2023) presents a simulation-based approach to guide decision-makers in selecting and validating multi-echelon inventory systems for distribution, a crucial aspect of multi-echelon distribution system optimization. The study acknowledges the increasing complexity of supply chains, making traditional analytical models less effective, and highlights simulation as a robust tool for assessing inventory strategy impacts. The proposed four-step approach involves characterizing the current supply chain, conceptually modeling various multi-echelon inventory system alternatives (such as installation stock vs. echelon stock policies and different safety stock allocation strategies), and finally, employing simulation software (Flexsim) for comparison and validation. The application to the Moroccan pharmaceutical supply chain demonstrated that an installation stock policy across all echelons, coupled with safety stock allocation at the most downstream stages, was the most appropriate alternative, balancing product availability and holding costs. While this study doesn't explicitly incorporate "time windows" or metaheuristic algorithms in its core simulation, its emphasis on comparing inventory policies and managing costs and product availability within a multi-echelon framework provides valuable insights for an undergraduate thesis focusing on optimizing multi-echelon distribution systems, especially when considering the indirect impacts of inventory decisions on delivery timeliness and overall system responsiveness.

Liu, S., & Zhang, C. (2022) addresses the optimization of cold chain distribution routes by incorporating mixed time windows and customer priority, a crucial aspect for multi-echelon distribution systems. It proposes a customer differentiation management strategy using a comprehensive evaluation index and the DBSCAN clustering algorithm to categorize customers by priority. The research constructs a mathematical programming model with a trapezoidal fuzzy number for time windows, aiming to minimize total costs, including fixed, green, penalty, refrigeration, and cargo damage costs. The model is designed for scenarios with and without inventory shortages, emphasizing the rational distribution of cold chain supplies and optimal route planning. An improved Evolutionary Algorithms, enhanced with a greedy algorithm-based crossover operator for better local search, is utilized to solve this NP-hard problem. The effectiveness of this approach is validated through a case study of imported fruit distribution in Xiamen City, demonstrating its ability to optimize routes for refrigerated trucks while considering customer priority and improving customer satisfaction without significantly increasing costs. While the paper focuses on a single distribution center, its methodology can be extended to multi-echelon systems by replicating the optimization logic across different stages.

Liu, Y., Yue, Z., Wang, Y., & Wang, H. (2023) the logistics distribution vehicle routing problem with time windows (VRPTW) by integrating a novel pallet 3D loading constraint, addressing issues of low loading rates and inefficient loading/unloading in express delivery. The core innovation lies in using telescopic-height pallets as intermediate carriers to enhance handling efficiency and space utilization, a concept applicable to multi-echelon systems requiring efficient inter-echelon transfers. The research formulates a dual-objective model to minimize total delivery cost and maximize vehicle loading rate, transforming it into a single-objective problem using a linear weighting method. To solve this, a hybrid simulated annealing-Evolutionary Algorithms is employed, combining spatio-temporal clustering for initial path optimization with a hierarchical approach for 3D pallet loading. The model's effectiveness is demonstrated through empirical data from an express company, showcasing improved loading rates and significantly reduced time window violation costs due to faster unloading processes enabled by the pallets. While the study primarily focuses on a single distribution center, its innovative approach to integrating 3D loading, time windows, and a metaheuristic algorithm for optimization offers valuable insights for designing and optimizing multi-echelon distribution systems, especially those dealing with diverse cargo types and strict delivery schedules.

Geevers, van Hezewijk, and Mes (2024) investigated deep reinforcement learning (DRL)—specifically the Proximal Policy Optimization (PPO) algorithm—to address multi-echelon inventory optimization (MEIO) by minimizing holding and backorder expenses. This methodology was tested on three distinct supply chain architectures: linear, divergent, and a general structure modeled after an actual manufacturer. A major advancement in this study is the implementation of a continuous action space for calculating replenishment volumes. This approach significantly boosts scalability for real-world logistical scenarios, offering a distinct advantage over the discrete action spaces traditionally favored in supply chain DRL applications. Experimental outcomes demonstrated that the PPO algorithm reliably surpassed conventional benchmarks across every evaluated network configuration. The framework yielded average cost reductions of 16.4% for linear systems, 11.3% for divergent setups, and 6.6% within the generalized manufacturing scenario. This study demonstrates the flexibility of

DRL as a metaheuristic approach for various supply chain configurations without requiring significant modifications or relying on extensive assumptions.

Qu, Huang, Nie, Fu, Ma, and Huang (2022) examined the simultaneous optimization of order allocation and inventory management within an omni-channel multi-echelon distribution network (OMDN) to foster sustainable and cost-effective logistics. Their research introduced a comprehensive inventory strategy that merges offline and online stock sharing at specific nodes with lateral transshipments across different facilities. Concurrently, they developed an order allocation framework aimed at cost minimization, factoring in variables like delivery distances, stock holding, replenishment expenses, and time-based penalties for delayed e-commerce orders. To resolve this intricate joint optimization problem, the authors utilized an Evolutionary Algorithm (EA). When evaluated against exact CPLEX solvers, the EA demonstrated significant proficiency in consistently generating near-optimal operational results. The numerical experiments show that the proposed strategy significantly reduces operational costs and improves the customer service level compared to alternative strategies, highlighting its economic, environmental, and social sustainability benefits. While the paper does not explicitly define fixed "time windows" for delivery in the same way as vehicle routing problems, it incorporates "time penalty cost" for extended delivery times for online orders, making it relevant for understanding time-sensitive aspects within multi-echelon distribution. The use of EA as a metaheuristic algorithm for this joint decision-making problem directly aligns with the thesis topic.

Ongcunaruk, W., Ongkunaruk, P., & Janssens, G. (2021) addresses a real-world vehicle routing problem with mixed time windows for a seasoning powder production company in Thailand, focusing on minimizing fixed vehicle costs, variable vehicle costs, and fuel costs. The problem is complex due to specific delivery time restrictions in Bangkok's metropolitan area, necessitating consideration of both normal and strict time windows. To overcome the computational limitations of a mixed-integer programming (MIP) model for large problem sizes, a Evolutionary Algorithms (EA) is developed. This EA incorporates a specialized initialization algorithm to generate feasible solutions and utilizes a partial factorial design to determine optimal parameter values. The study demonstrates that the EA significantly reduces computational time (by 67.78% to 99.45%) while achieving near-optimal solutions (within a 0-0.21% EAp from MIP). While the study focuses on a single-depot vehicle routing problem rather than a multi-echelon system, its effective use of a EA to optimize routing with mixed time windows and its emphasis on cost minimization make it a relevant reference for metaheuristic applications in time-window-constrained distribution, particularly for aspects concerning vehicle routing within an echelon.

Chen, C. and Wu, S. (2021) addresses the shortcomings of traditional Evolutionary Algorithms for solving logistics distribution problems by proposing an improved Evolutionary Algorithms to optimize the Vehicle Routing Problem with Time Windows (VRPTW), considering both vehicle load and time constraints. The study's method preserves the best genes during the crossover process to enhance convergence speed and designs a mutation operation to maintain population diversity, thereby reducing the number of infeasible solutions. The research was implemented on Matlab 2016, and its simulation experiments demonstrated that the improved Evolutionary Algorithms reduced transportation costs by about 10% compared to the traditional version. The algorithm effectively avoids local optima and provides a more reasonable vehicle route, thereby proving its superiority and effectiveness for solving this type of problem. This paper directly supports the thesis by providing a clear example of applying and improving a Evolutionary Algorithms to a VRPTW model, which is highly relevant to the subject of multi-echelon distribution with time windows.

Wu, W., Zhou, W., Lin, Y., Xie, Y., & Jin, W. (2021) focuses on the Location Inventory Routing Problem (LIRP), a complex optimization challenge in logistics that jointly addresses location, vehicle routing, and inventory plans in multi-echelon systems. It highlights that traditional, sequential approaches to these problems are suboptimal due to their interdependencies, leading to the development of integrated models like the LIRP. The paper aims to improve upon existing LIRP models by incorporating realistic factors such as time windows, vehicle fuel consumption, and allowing for stock-out situations at retailers. Methodologically, the study proposes a custom-designed Evolutionary Algorithms to solve this NP-hard problem, which is further refined with a post-optimization method based on a gradient descent algorithm to enhance the replenishment plans.

Wang, C. N., Nhieu, N. L., Chung, Y. C., & Pham, H. T. (2021) developed a multi-objective mathematical model to design a four-echelon intermodal perishable supply chain for fresh fruits, focusing on a sustainable balance of economic, environmental, and social pillars. The research's objective functions aim to minimize operational expenses, transit durations, environmental emissions, and temporal discrepancies between supply and demand. To manage this complexity, the authors introduced an innovative methodology that consolidates these competing goals into a single weighted objective function, utilizing priorities established through comprehensive surveys of industry experts and stakeholders. This mathematical framework was then deployed within the fresh fruit sector of Vietnam's Mekong Delta. It effectively guided strategic choices regarding facility placement, capacity, and workforce allocation, alongside tactical routing decisions. Ultimately, the results illustrated how modifying priority weights fundamentally alters the supply chain's configuration, highlighting the inherent compromises required to balance economic efficiency with ecological sustainability.

Miao, Y. and Bao, X. (2025) focus on an improved Evolutionary Algorithms for the Semi-Soft Clustered Vehicle Routing Problem (SemiSoftCluVRP), a novel VRP variant that generalizes the existing Clustered VRP (CluVRP) and Soft CluVRP. The SemiSoftCluVRP partitions customers into two types of clusters: hard clusters, which require uninterrupted service from a single vehicle, and soft clusters, which allow for service interruptions by the same vehicle. To solve this, the researchers developed a two-level Evolutionary Algorithms that integrates a variable neighborhood descent (VND) method. The algorithm decomposes the problem into a high-level Capacitated VRP (CVRP) for clusters and a low-level Traveling Salesman Problem (TSP) for customers within each cluster. Computational experiments using 77 instances demonstrated that the proposed algorithm can reduce logistics costs by up to 6.50% compared to CluVRP, while also showing a cost increase of up to 7.52% compared to SoftCluVRP, depending on the attributes of the clusters. The flexibility of adjusting hard and soft cluster attributes provides a more practical decision-making tool for real-world scenarios.

Liu, Tong, and Xia (2025) introduced an advanced Evolutionary Algorithm, designated as CLCS-EA, to address the Vehicle Routing Problem with Time Windows (VRPTW), which remains a fundamental challenge in logistics optimization. To elevate the algorithm's computational efficiency, the authors incorporated a series of innovative methodological strategies. Initially, they deployed a hybrid initialization technique that groups clients according to spatial coordinates and delivery schedules, generating three separate subpopulations to accelerate the convergence rate. Furthermore, the model utilizes the Longest Common Substring (LCS) extracted from both high-performing and underperforming solutions to direct the mutation and crossover phases. This ensures that advantageous genetic sequences are retained while ineffective traits are eliminated, thereby preventing the model from stagnating in local optima. Lastly, the researchers refined the local search phase by evaluating customer interconnectedness—relying on spatial closeness and temporal constraints—to mitigate the inherent randomness typical of conventional local search methods. The comprehensive performance of CLCS-EA was validated using 56 VRPTW instances, and its strategies were shown to be effective compared to other algorithms.

Johar, F., Zawawi, N. S. M., and Nordin, S. Z. (2024) focus on maximizing the supply chain profit in a multimodal transportation network that includes a transfer part and a specified time window. The research utilizes a mathematical programming model to optimize a three-stage supply chain involving a manufacturer, a distribution hub, and a market. This model considers five key factors: production cost, transportation cost, transport time, penalty cost for early or late deliveries, and sales price. To solve this optimization problem, the study proposes a Two-Echelon Evolutionary Algorithms (TEEA), a heuristic approach that is more efficient for complex, large-scale problems than exact methods. The results demonstrate that the proposed TEEA outperforms a previous exact solution by yielding a higher maximum profit of 52,832 compared to 52,026, confirming its efficiency and robustness.

Table 2. 1 Literature Review

No	Author	Method			Research Focus
		Multi-Echelon Distribution System	Time Window Constraint	Evolutionary Algorithm	
1	Awwalu, H. B., Abdullahi, N., & Hussaini, M. (2023)	√		√	Multi-echelon distribution system, Evolutionary Algorithms
2	DERSE, O., & GÖÇMEN, E. (2023)	√			Multi-echelon distribution systems
3	Wang, Z., & Wen, P. (2020)	√	√	√	Two-echelon distribution system, mixed time windows, Adaptive Evolutionary Algorithms.

4	Sbai, N., & Berrado, A. (2023)	√			Multi-echelon distribution systems
5	Liu, S., & Zhang, C. (2022)	√	√		Mixed time windows, Multi-echelon distribution systems.
6	Liu, Y., Yue, Z., Wang, Y., & Wang, H. (2023)		√	√	Time Window, Evolutionary algorithm.
7	Geevers, K., van Hezewijk, L., & Mes, M. R. K. (2024)	√			Multi-echelon inventory optimization (MEIO)
8	Qu, T., Huang, T., Nie, D., Fu, Y., Ma, L., & Huang, G. Q. (2022)	√		√	Multi-echelon distribution, Evolutionary Algorithms.
9	Ongcunaruk, W., Ongkunaruk, P., & Janssens, G. (2021)	√		√	mixed time windows, Evolutionary Algorithms method.
10	Chen, C. and Wu, S. (2021)		√	√	Evolutionary Algorithms
11	Wu, W., Zhou, W., Lin, Y., Xie,	√		√	Multi-echelon distribution systems,

	Y., & Jin, W. (2021)				Evolutionary Algorithms
12	Wang, C. N., Nhieu, N. L., Chung, Y. C., & Pham, H. T. (2021)	√			Multi-echelon distribution system
13	Miao, Y. and Bao, X. (2025)			√	Evolutionary Algorithms
14	Liu, J., Tong, L., and Xia, X. (2025)		√	√	Evolutionary Algorithms, Time window constraint
15	Johar, F., Zawawi, N. S. M., and Nordin, S. Z. (2024)	√	√	√	Time window constraint, Two-Echelon distribution system, Evolutionary Algorithms

2.2 Empirical Study

2.2.1 Multi-Echelon Distribution Systems

Multi-echelon distribution system refers to a logistics network composed of multiple hierarchical levels (or echelons) through which products flow from suppliers or manufacturers to end customers. Each echelon such as central warehouses, regional distribution centers, and retailers plays a specific role in storing, handling, and transporting goods to meet demand efficiently across various geographic regions. In a multi-echelon system, inventory and transportation decisions must be coordinated across different levels to minimize total logistics costs while ensuring service level requirements are met. Unlike single-echelon systems that involve direct shipments from a central location to end customers, multi-echelon structures offer greater flexibility and scalability but come with increased complexity in planning and optimization (Simchi-Levi et al., 2022). These systems are commonly used in industries with broad distribution networks, such as retail, food and beverage, pharmaceuticals, and e-commerce.

According to (Ech-Cheikh, Douraid & El Had, 2020) Effectively managing multi-echelon distribution systems requires a comprehensive understanding of various foundational elements that dictate the complexity of the operational problem. Key characteristics that must be defined include the underlying network architecture, specific inventory control mechanisms, stock allocation procedures, overall system governance, targeted customer service levels, and fluctuating demand patterns.

The following figure 1 highlights those characteristics:

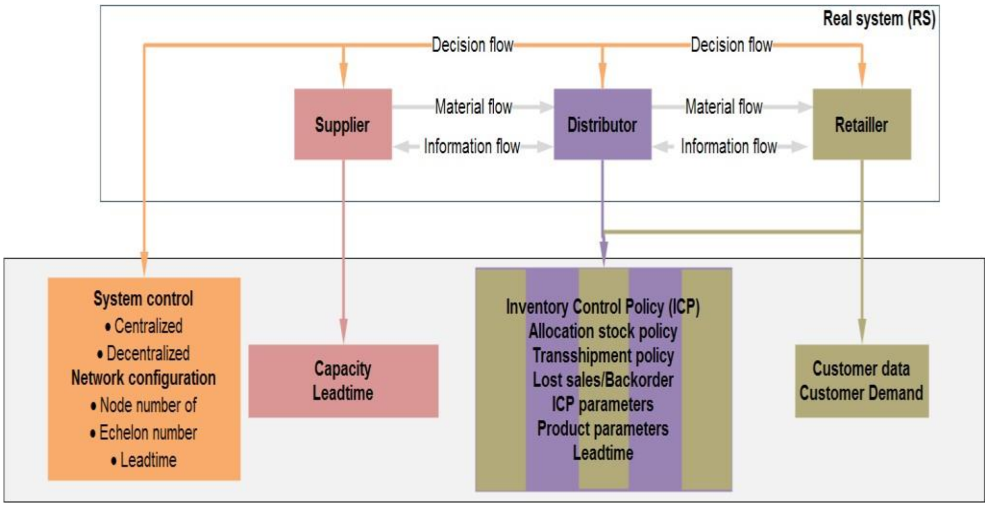


Figure 2. 1 Multi-Echelon Distribution System Characteristics.

Source: Hamid Ech-Cheikh, 2020

a. Network Structure

The fundamental trait of a Multi-Echelon Distribution System (MEDS) is a hierarchical flow where upstream entities supply downstream stages. However, real-world applications often feature variations, such as lateral transshipments between facilities at the same tier, which can blur the boundaries between echelons. According to academic literature, four primary structural classifications exist:

1) Serial Configurations: Characterized by a linear sequence where each echelon consists of exactly one physical location.

2) Divergent (Arborescent) Systems: A branching network where each facility

receives inventory from a single source but may distribute to multiple downstream nodes.

3) Convergent Systems: A structure where a single facility is supplied by multiple upstream stages but serves only one specific downstream location.
4) General (Mixed) Networks: A sophisticated architecture that integrates elements of both divergent and convergent systems, creating complex, multi-path supply chains.

b. Inventory Control Policy

A robust inventory control framework is typically constructed around three critical decision-making pillars:

1) Establishing the optimal order quantity (Q) to balance holding and setup costs.
2) Defining the reorder point (r), which identifies the specific inventory threshold that necessitates a new replenishment.
3) Determining the review interval (T), or the frequency at which stock levels are audited.

These frameworks are categorized into two operational methodologies:

1) Continuous review policies: EOQ, (S, S-1), (Q, r), order-up-to, and (S, s).

In these models, inventory levels are monitored in real-time. Key variations include the Economic Order Quantity (EOQ) for stable environments; the Base-Stock (S, S-1) policy, where an order is triggered by every individual demand instance; and the (Q, r) policy, where a fixed volume (Q) is ordered once the reorder point (r) is reached. Another variation is the (S, s) policy, which targets a maximum stock level (S) but utilizes variable order quantities depending on the deficit when stock hits the minimum threshold (s).

2) Periodic review policies

These systems involve checking inventory levels at discrete, fixed time intervals (T). Policies like (T, S) or (T, S, s) function similarly to their continuous counterparts but only allow for ordering at specific cycle lengths. This approach is often used when coordinating shipments with transportation schedules or when manual audits are required.

c. Control System

The governance and control architectures within multi-echelon distribution networks are primarily categorized into two distinct operational paradigms: centralized and decentralized systems. Frequently, these multi-tier networks operate under a decentralized framework, meaning that inventory management and replenishment decisions are executed strictly at the local installation level. Within such a decentralized configuration, every individual retailer or downstream facility independently generates and submits its own purchase orders directly to an external supplier. A significant operational advantage of utilizing this specific installation stock policy is its inherent simplicity; it operates efficiently without necessitating real-time inventory visibility or data sharing across other network nodes, which is highly beneficial when system-wide information is unavailable or restricted.

Conversely, within a centralized control architecture, the critical functions of inventory allocation and stock replenishment are managed holistically by the primary supplier or a central command hub. A prominent methodology to achieve this comprehensive network control is through the implementation of an echelon stock policy. Because ordering decisions within an echelon-based framework rely on a complete and accurate understanding of the inventory status at all subsequent downstream stages, seamless data integration and continuous information sharing among all participating nodes become absolute prerequisites for operational success.

d. Multi-echelon dechotomies

Multi-echelon supply chains are inherently intricate and fluid networks. Operating within volatile environments introduces a multitude of unpredictable variables across the entire logistical chain. Critical elements such as fluctuating consumer demand, variable delivery lead times, complex routing processes, dense inter-node relationships, and rigid supply limitations constitute the primary sources of continuous, unpredictable change that researchers must carefully address. Crucially, these variable factors do not remain static; they evolve persistently, exerting a profound and measurable influence on the overall operational success and performance of the distribution network. To effectively analyze these systemic intricacies, academic models frequently categorize them into several foundational operational dichotomies:

1) Deterministic versus Stochastic Environments: Within a purely deterministic

framework, critical operational parameters including customer demand, transit lead times, and facility capacities at any specific node are treated as absolute, pre-established constants known with complete certainty. Conversely, a stochastic modeling approach acknowledges the inherent randomness of real-world logistics, representing these fluctuating demands, lead times, and capacities as variables that operate within the bounds of specific probability distributions.

2) Single-Product versus Multi-Product Dynamics: A single-product analytical model focuses exclusively on the flow of one distinct item type, intentionally omitting any potential resource conflicts or interactions with alternative goods. In contrast, a multi-product framework evaluates the simultaneous distribution of diverse goods, deliberately accounting for how these different items compete for shared, constrained resources, such as strict financial budgets or limited warehouse storage capacities.

3) Backlogging versus Lost Sales Protocols: This dichotomy defines the systemic response to inventory stockouts. A backlogging model operates on the assumption that any unfulfilled customer demand is temporarily recorded and eventually satisfied during subsequent replenishment cycles. Under the lost sales paradigm, however, the system assumes that any demand unable to be met immediately is permanently forfeited, with no possibility of future recovery or retention.

2.2.2 Supply Chain Network Design (SCND)

Supply Chain Network Design (SCND) represents a foundational element of comprehensive supply chain management, focusing primarily on the strategic architecting of both physical infrastructure and associated decision-making frameworks. This intricate process involves establishing the optimal quantity, geographical placement, and operational capacity of critical network nodes, including manufacturing plants, centralized warehouses, and regional distribution centers. Furthermore, SCND dictates the strategic assignment of customer demand zones and orchestrates the efficient, cost-effective routing of materials and finished goods throughout these interconnected facilities. The main objective of SCND is to design a network that minimizes total cost—comprising transportation, inventory, facility, and operational costs while simultaneously meeting service level requirements and customer expectations (Melo, Nickel, & Saldanha-da-EAma, 2009).

In the context of a multi-echelon distribution system, SCND plays a central role because it directly affects the flow of goods across multiple stages such as central warehouses, regional distribution centers, and retailers. These multi-echelon systems must be designed not only to optimize costs but also to maintain delivery performance under various constraints, including time windows. Time windows are predefined periods within which deliveries must be made, and they are crucial for ensuring customer satisfaction and operational efficiency (Cruz et al., 2017).

Research has shown that the integration of time-sensitive constraints like delivery time windows significantly increases the complexity of SCND problems. Traditional linear models often fall short in handling such complex, nonlinear, and multi-objective problems. Therefore**,** metaheuristic algorithms, particularly Evolutionary Algorithms (EAs)**,** have gained popularity in solving SCND problems. Altiparmak et al. (2006) demonstrated the effectiveness of EA in multi-objective supply chain network design problems, where the algorithm successfully balanced conflicting goals such as cost minimization and service level maximization. EA is particularly suitable because of its robustness, adaptability, and capacity to explore a large solution space efficiently (Goldberg, 1989).

Moreover, Shen (2007) emphasized the need for SCND models that incorporate demand uncertainty and delivery constraints, suggesting that models need to be flexible and capable of dynamic adjustments. In Indonesia’s context, where distribution inefficiencies are still prevalent—due to infrastructure limitations, long delivery times, and high logistics costs (World Bank, 2021)—a robust SCND model becomes increasingly necessary. This makes the adoption of intelligent algorithms such as EA not just theoretically sound, but also practically relevant.

Additionally, SCND contributes significantly to strategic decision-making. It provides a structured way for firms to plan expansions, minimize response time, and enhance customer service. The impact of a well-designed SCND is especially evident in warehousing and distribution companies that operate across different regions and time zones. These companies often face challenges related to coordinating supply and demand across a distributed network. Implementing SCND with time window constraints allows them to fine-tune operations and remain competitive in a fast-paced market environment.

In summary, Supply Chain Network Design is a foundational theory in optimizing complex distribution systems, particularly multi-echelon structures with strict time constraints. Its integration into your research provides a solid theoretical and methodological basis for applying Evolutionary Algorithms as an optimization approach. Through SCND, your research aligns with both academic findings and real-world challenges, particularly in the Indonesian logistics landscape.

2.2.3 Inventory Management

Inventory management serves as a critical cornerstone within supply chain logistics, dedicated to the systematic regulation, oversight, and refinement of product levels throughout the entire distribution network. Its primary objective is to guarantee that the precise volume of merchandise is strategically positioned at the correct facility and exact moment to fulfill consumer requirements, all while rigorously mitigating the financial burdens associated with excess storage and stockout penalties. Effective inventory management becomes especially critical in multi-echelon distribution systems, where inventory is held at multiple points, such as central warehouses, regional distribution centers, and retail outlets (Axsäter, 2006).

In a multi-echelon context, inventory management becomes significantly more complex due to the interdependencies between different echelons. Inventory decisions at an upstream facility (e.g., central warehouse) directly influence stock availability and replenishment requirements at downstream facilities (e.g., regional warehouses and retailers). This requires a coordinated approach to ensure that inventory levels are optimized across all echelons to avoid both stockouts and excessive holding costs (Simchi-Levi, Kaminsky, & Simchi-Levi, 2008).

Several models have been developed to manage multi-echelon inventory systems, such as the echelon stock model, base stock policies, and (s, Q) policies. However, these classical models often rely on simplifying assumptions such as deterministic demand or infinite capacity, which are rarely applicable in real-world scenarios. Furthermore, these models typically do not account for time window constraints, which are increasingly important in modern supply chains where customers demand not only product availability but also timely delivery (Chen & Lee, 2002).

To address these complexities, researchers have turned to intelligent optimization methods, including Evolutionary Algorithms (EA). EA has been proven effective in solving inventory optimization problems, particularly in stochastic and multi-objective environments. For instance, Khouja (1999) demonstrated the utility of EA in solving the Economic Order Quantity (EOQ) model under uncertain conditions. Similarly, Xu et al. (2012) applied EA to optimize inventory placement and replenishment strategies in a multi-echelon network, achieving better performance than traditional heuristic methods.

Moreover, integrating inventory management with distribution system design enhances the performance of the entire supply chain. By jointly considering inventory decisions and distribution planning, companies can achieve significant cost savings and service level improvements. In Indonesia, where inefficiencies in logistics and inventory handling persist—such as long lead times and high obsolescence rates (World Bank, 2021)—intelligent inventory management is critical to overcoming structural and operational challenges.

Inventory management also plays a strategic role in aligning supply chain activities with business goals. By maintaining optimal stock levels, companies can reduce their capital tied up in inventory, increase responsiveness to market changes, and enhance customer satisfaction. These benefits are especially important for warehousing companies, the focus of this research, which operate as intermediaries between manufacturers and retailers and must manage fluctuating inventory levels while adhering to delivery time windows.

In conclusion, inventory management is not just an operational function but a strategic lever in optimizing multi-echelon distribution systems. Its integration into this research framework strengthens the study’s foundation by addressing both the flow and availability of goods across the supply chain. Coupled with the Evolutionary

Algorithms, inventory management serves as a powerful tool for developing efficient, adaptive, and time-sensitive logistics systems.

2.2.4 Transportation Management

Transportation management is another critical component in the design and optimization of multi-echelon distribution systems, especially when time windows are enforced. Transportation activities link various nodes in the supply chain—from suppliers to warehouses to retailers—impacting delivery reliability, inventory levels, and overall logistics costs. Efficient transportation management ensures that products are moved in a timely and cost-effective manner, directly supporting service-level goals and operational efficiency (Christopher, 2016).

In multi-echelon distribution systems, transportation must be planned across multiple tiers, considering both inbound and outbound flows. Each echelon may have different delivery schedules, capacities, and service level agreements, making transportation coordination a complex task. The incorporation of time windows adds to this complexity, as deliveries must be made within a specific time range to avoid delays, penalties, or loss of customer trust (Cordeau et al., 2007).

Transportation costs typically constitute a significant portion of total logistics expenses. Thus, optimizing routes, shipment sizes, and scheduling is essential to reducing operational costs. In this context, Vehicle Routing Problems with Time Windows (VRPTW) are often used to model transportation decisions within a multi-echelon system. These models aim to minimize total distance traveled or total delivery cost while meeting customer time window requirements.

Given the NP-hard nature of VRPTW and the complexity of multi-echelon systems, Evolutionary Algorithms (EA) have become increasingly popular for solving such problems. EA can be used to encode route combinations and schedules into chromosomes and evolve these solutions through crossover, mutation, and selection to find optimal or near-optimal routing plans (Prins, 2004). This metaheuristic approach is particularly useful when conventional exact methods become computationally infeasible due to the large scale and complexity of the problem.

Incorporating transportation management theory into the optimization model for this research ensures a more realistic representation of real-world distribution challenges. It also allows the developed model to consider practical aspects such as route planning, vehicle capacities, and time-sensitive deliveries—further enhancing its applicability for warehousing and distribution companies operating in dynamic markets.

2.2.5 Time Window Constraint

Time window constraints represent a critical aspect in the optimization of modern distribution systems, especially within multi-echelon supply chains. A time window refers to a specific period during which a delivery or pickup must occur. These constraints are commonly imposed by customers or distribution nodes to ensure service level expectations are met and operations remain synchronized (Cordeau et al., 2001).

In the context of multi-echelon distribution systems, the complexity of time windows increases significantly. Each echelon—whether it be manufacturers, central warehouses, regional distribution centers, or retailers—can have its own time-related service requirements. These may include operating hours, preferred delivery slots, and buffer times to manage inbound and outbound flows. Failing to meet these time constraints can lead to significant operational disruptions, customer dissatisfaction, and even financial penalties (Tan et al., 2010).

From a modeling perspective, time windows introduce temporal constraints that must be satisfied in addition to spatial or quantity-based constraints. These often make the problem NP-hard, especially when combined with other logistics components such as inventory decisions, transportation routing, and facility location. Thus, incorporating time windows into the optimization framework ensures that solutions are not only cost-efficient but also operationally feasible and customer-centric (Desaulniers et al., 2002).

Given the difficulty of solving such complex problems using traditional optimization techniques, metaheuristic algorithms like the Evolutionary Algorithms (EA) offer a powerful alternative. EA can be designed to evolve solutions that respect time window constraints by applying penalty functions to infeasible schedules or by integrating repair mechanisms that adjust violations during evolution. Several studies have demonstrated the effectiveness of EA in solving Vehicle Routing Problems with Time Windows (VRPTW) and Time-Constrained Distribution Scheduling Problems (Solomon, 1987; Liu et al., 2009).

By incorporating time window constraints into this research, the optimization model will better reflect real-world challenges faced by distribution and warehousing companies, particularly in ensuring on-time deliveries across multiple echelons. This aligns with growing expectations for timely logistics services in fast-paced markets, such as in Indonesia, where on-time delivery is a key competitive advantage.

2.2.6 Metaheuristic Algorithm: Evolutionary Algorithms

Metaheuristic algorithms are optimization methods designed to solve complex problems that are otherwise intractable using traditional exact techniques. Among these, the Evolutionary Algorithms (EA) has emerged as a prominent approach due to its robustness and flexibility in handling large-scale, nonlinear, and multi-constrained problems typically found in supply chain and distribution system optimization (Holland, 1975; Haupt & Haupt, 2004).

Evolutionary Algorithms draw fundamental inspiration from the principles of biological natural selection, functioning across a diverse population of candidate solutions. Within this computational framework, every individual member acts as a prospective answer, structurally encoded as a chromosome. The methodology progressively refines this solution pool through specialized genetic operators—namely selection, crossover (recombination), and mutation. This iterative evolution is continuously directed by a fitness function, which rigorously measures and ranks the relative quality of each proposed solution (Goldberg, 1989).

In the context of multi-echelon distribution systems with time window constraints, EA is highly suitable due to its capability to search a large and complex solution space effectively without being trapped in local optima. Unlike exact methods such as Mixed-Integer Linear Programming (MILP), which may struggle with computational limits as the problem size grows, EA maintains reasonable performance even for high-dimensional and combinatorially complex supply chain problems (Gen & Cheng, 2000).

Several researchers have successfully applied EA in logistics and supply chain domains. For instance, Liu et al. (2009) utilized EA to solve the Vehicle Routing Problem with Time Windows (VRPTW), demonstrating its ability to generate feasible and cost-effective routing plans under delivery constraints. Similarly, Srivastava (2008) employed EA for multi-echelon inventory optimization, proving its effectiveness in balancing inventory costs and service levels across multiple stages.

For this research, EA will be used to optimize the distribution flows within a multi-echelon structure, considering warehouse capacity**,** transportation limitations, and time window constraints. The algorithm will be customized to ensure that each generated solution respects the complex interplay between delivery schedules and cost minimization, providing a flexible yet efficient framework for solving the real-world distribution problem faced by the warehousing company under study.

By incorporating a Evolutionary Algorithms, this research benefits from a proven metaheuristic method capable of producing near-optimal solutions within a reasonable computation time. Its adaptability makes it especially suitable for industrial applications where data complexity, uncertainty, and time sensitivity are key concerns.

2.2.7 Bullwhip Effect

The Bullwhip Effect represents a widely recognized operational challenge within supply chain networks. It occurs when minor shifts in consumer purchasing behavior at the retail tier trigger progressively amplified demand distortions as orders move upstream through wholesalers, manufacturers, and raw material suppliers (Lee, Padmanabhan, & Whang, 1997). Consequently, this amplification severely degrades overall network efficiency, leading to detrimental outcomes including surplus stockpiles, critical inventory shortages, inflated operational expenditures, and diminished consumer satisfaction metrics.

The Bullwhip Effect typically arises from several key causes: demand signal processing, order batching, price fluctuation, and lack of information sharing across the supply chain (Forrester, 1961). When individual members of the supply chain base their decisions on their own demand forecasts rather than actual customer demand, information distortion occurs. This leads to overreaction in ordering behavior and amplifies variability further up the supply chain.

In multi-echelon distribution systems, the Bullwhip Effect can be particularly severe due to the presence of multiple stages and intermediaries, each with their own ordering policies and lead times. The complexity is further exacerbated when time window constraints are introduced, which restrict the allowable delivery periods and can lead to inefficient order timing or rushed shipments. This interplay between echelon levels and time sensitivity increases the risk of demand distortion and inventory imbalance (Chen et al., 2000).

Several strategies have been proposed in the literature to mitigate the Bullwhip Effect, including information sharing, synchronized planning, demand smoothing, and the use of advanced forecasting and optimization algorithms. One promising approach is the integration of metaheuristic algorithms, such as Evolutionary Algorithms, which can optimize ordering and distribution decisions across multiple echelons while incorporating constraints like time windows and capacity limitations (Tako & Robinson, 2012).

In this research, understanding the Bullwhip Effect is crucial for modeling realistic supply chain dynamics in the optimization of multi-echelon distribution systems with time windows. By acknowledging the potential for demand amplification and incorporating robust optimization strategies, the model can more accurately reflect operational realities and offer solutions that reduce inefficiencies and improve overall supply chain responsiveness.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Research Subject and Research Object Design

"The subject of a research study serves as the central topic or phenomenon that the inquiry is designed to investigate and analyze. It defines the scope of the study and focuses the research efforts on a specific area to develop new knowledge or verify existing theories" (Creswell & Creswell, 2018; Denscombe, 2017; Saunders et al., 2019). In this research the research subject is the application and performance evaluation of a Evolutionary Algorithms for optimizing a two-echelon distribution system with time window constraints.

The "object" is the specific entity, product, or construct that is being investigated or created in order to fulfill the research's objective. It is the tangible focal point of the study, which can be a system, a model, a methodology, or a dataset, and it represents the means by which the research subject is explored (Bryman, A., & Bell, E. 2018). In this research a computational model, implemented in Microsoft Excel with VBA, designed to optimize the vehicle routing and scheduling of PT. POS INDONESIA’s distribution network. The model will determine the most cost-effective routes for their vehicles, starting from their main location at Jl. Kebagusan Raya No.44, to customer locations while respecting specific time windows and vehicle capacity."

3.2 Data Collection Method

To fulfill the objectives of this research, specific categories of information were systematically gathered. The distinct classifications and precise origins of the data utilized throughout this study are detailed as follows:

1. Primary Data

   Primary data encompasses original, firsthand information systematically gathered directly by the investigator to address the specific objectives of the current research. This data is unique to the research project and is gathered through a controlled methodology to address a specific research question.

2. Secondary Data

   Secondary data is used to build the theoretical and methodological foundation of the study. This includes a review of peer-reviewed journals, books, and academic conference papers to establish the conceptual framework for concepts like distribution system, Evolutionary Algorithms, and time window constraint. Additionally, secondary data is acquired from a third party in the form of two years of distribution system at PT. POS INDONESIA warehousing company, which is used to support the research's empirical analysis.

3.3 Research Instrument

This section presents to systematically gather the necessary information to address the research questions and objectives. The choice of instrument depends on the type of data being collected and the research methodology. In this research quantitative studies are chosen, this could be a structured data collection plan, such as a log to record sales data from a third party. Essentially, the research instrument is the mechanism through which the researcher bridges the gap between the research question and the evidence needed to answer it. The selected research instruments play a critical role in acquiring both the primary and secondary data necessary to accurately map the distribution network of the subject warehousing enterprise. This specific organization is primarily responsible for the logistical movement of products to various retail outlets and direct consumers. Within the scope of this research, these instruments are defined as the specific technical tools and systematic methodologies applied to drive the investigation forward. They comprehensively support every phase of the research workflow, including the initial gathering of raw information, the computational processing and analytical evaluation of that data, and the final academic documentation. Specifically, the key instruments deployed to conduct this study include the following:

1. Laptop:

   A personal computing device served as the primary hardware platform for the entirety of this research endeavor. Its continuous utility spanned multiple critical phases of the study, encompassing the initial drafting of the manuscript, the secure organization and storage of essential datasets, the execution of complex computational algorithms for data processing, and the ultimate synthesis and compilation of this final academic thesis.

2. Microsoft Excel and VBA

   This software platform is used to house the model's data, constraints, and objective function. Custom scripts written in VBA automate the process of the Evolutionary Algorithms (EA), including generating the initial population, performing genetic operations, and evaluating the fitness of solutions.

3. Excel Solver

   This is the core engine that runs the Evolutionary Algorithms to find an optimal solution by iteratively refining potential delivery routes. It systematically explores the solution space to identify the most efficient route plan for the multi-echelon distribution system.

4. Diagrams.net

   This web-based diagramming application was utilized to construct comprehensive flowcharts that provide a clear visual representation of the entire research methodology. It served as a critical instrument for illustrating the sequential progression of the study, meticulously mapping out the procedural steps starting from the initial data collection and input phases, proceeding through the computational analysis using the evolutionary algorithm, and ultimately culminating in the synthesis of final conclusions and strategic recommendations.

3.4 Mathematical Model Development in Excel

To bridge the gap between the theoretical formulation and the practical optimization, the mathematical model is developed within a spreadsheet environment. This stage involves translating the mathematical notations (indices, parameters, and decision variables) into a structured Excel architecture that the Solver can interact with.

3.4.1 Sets and Indices

The mathematical model utilizes the following sets and indices to represent the distribution network:

- N: Set of all nodes, where $N = C \cup D$.
- C: Set of customers (retailers), indexed by $i, j \in \{1, 2, ..., n\}$.
- D: Set of depots (overflow warehouses), indexed by $d \in \{n+1, ..., n + m\}$.
- K: Set of available vehicles, indexed by $k \in \{1, ..., v\}$.
- 0: Represents the starting node (origin) at the depot.

3.4.2 Parameters

The following parameters represent the fixed input data used in the optimization:

- d_{ij}: The distance (cost) between node i and node j.
- q_i: The demand (weight) required by customer i.
- Q: The maximum weight capacity of each vehicle.
- s_i: The service time (unloading time) required at customer i.
- t_{ij}: The travel time between node i and node j.
- $[e_i, l_i]$: The Time Window for customer i, where e_i is the earliest allowed arrival time and l_i is the latest allowed arrival time.

3.4.3 Decision Variables

The model optimizes the values of the following decision variables:

1. Routing Variable (x_{ijk}): A binary variable.

$$x_{ijk} = \begin{cases} 1 & If vehicle\ k\ travels\ directly\ from\ node\ i\ to\ node\ j \\ 0 & otherwise \end{cases}$$

2. Time Variable (a_{ik}): A continuous variable representing the arrival time of vehicle k at node i.
3. Load Variable (u_{ik}): A continuous variable representing the remaining load of vehicle k upon arrival at node i.

3.4.4 Objective Function

The primary objective is to minimize the total distance traveled by the entire fleet.

$$\boldsymbol{Minimize\ Z} = \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} \boldsymbol{d_{ij}} \cdot \boldsymbol{x_{ijk}}$$

3.4.5 Constraints

The objective function is subject to the following constraints which ensure the solution is feasible:

1. Assignment Constraint:

Each customer *i* must be visited exactly once by exactly one vehicle.

$$\sum_{k\in K}\sum_{j\in N} \boldsymbol{x_{ijk}} = \mathbf{1}, \quad \nabla\mathbf{i} \in C$$

2. Flow Conservation:

If a vehicle *k* arrives at customer node *h*, it must also depart from node *h*.

$$\sum_{i\in N} \boldsymbol{x_{ihk}} - \sum_{j\in N} \boldsymbol{x_{hjk}} = \mathbf{0}, \quad \nabla\boldsymbol{h} \in C,\ \nabla\boldsymbol{k} \in \boldsymbol{k}$$

3. Capacity Constraint:

The total demand carried by any vehicle *k* on its route must not exceed the vehicle capacity *Q*.

$$\sum_{i\in c} \boldsymbol{q_i} \sum_{j\in N} \boldsymbol{x_{ijk}} \leq \boldsymbol{Q}, \quad \nabla\boldsymbol{k} \in \boldsymbol{K}$$

4. Time Window Constraints:

The arrival time at node *j* must be feasible relative to the departure from the previous node *i*, accounting for service time (s_i) and travel time (t_{ij}).

$$\boldsymbol{x_{ijk}} \cdot \left(\boldsymbol{a_{ik}} + \boldsymbol{s_i} + \boldsymbol{t_{ij}}\right) \leq \boldsymbol{a_{jk}}, \quad \nabla\mathbf{i}, \mathbf{j} \in \boldsymbol{N}, \nabla\mathbf{k} \in \mathbf{K}$$

Additionally, the arrival time must fall within the customer's specified time window.

$$\boldsymbol{e_i \leq a_{ik} \leq l_i}, \quad \boldsymbol{\nabla i} \in \boldsymbol{N}, \boldsymbol{\nabla k} \in \boldsymbol{K}$$

5. Depot Flow:

Each route used must start and end at the same designated depot.

$$\sum_{j \in C} \boldsymbol{x_{djk}} \leq \mathbf{1}, \quad \boldsymbol{\nabla d} \in \boldsymbol{D}, \boldsymbol{\nabla k} \in \boldsymbol{K}$$

3.5 Research Flow

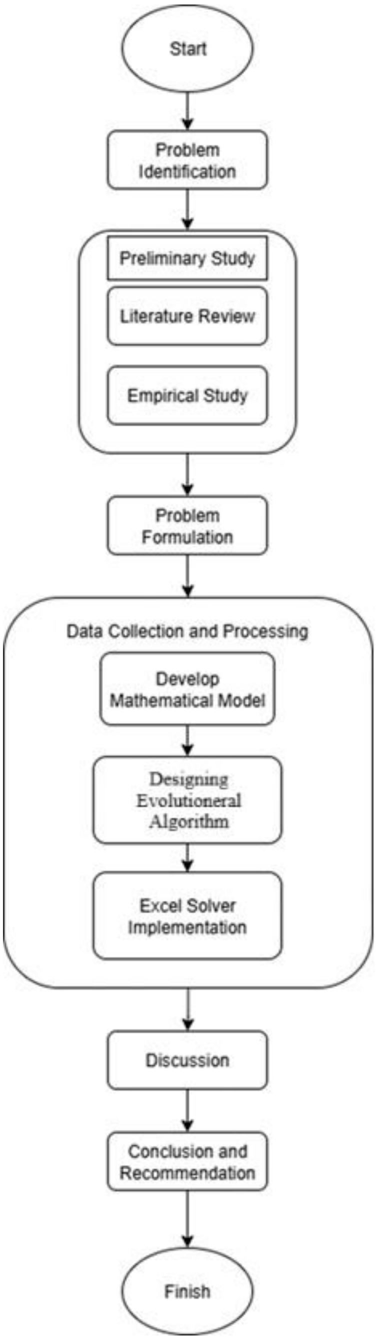


Figure 3. 1 Research Flowchart

The following is an explanation of the research flow diagram in Figure 3.1 above.

1) Problem Identification

   Identify inefficiencies in current distribution system methods and explore the use of evolutionary algorithm to optimize the distribution system

2) Preliminary Study

The preliminary study is structured into two main components: inductive and deductive. The inductive study involves reviewing previous academic journals to find a theoretical basis for the research and to support the preparation of the final report. The deductive study, on the other hand, focuses on gathering foundational knowledge from books and other sources. This includes a comprehensive understanding of concepts like Supply Chain Management, Multi-Echelon Distribution Systems, Inventory Management, and Evolutionary Algorithms (EA).

3) Problem Formulation

Information gathered on the current issues at PT. POS INDONESIA will be used to formulate a problem statement. This formulation will subsequently guide the determination of the research's objectives and benefits.

4) Data Collection and Processing

a) Organize distribution systems route data, with 1 main warehouse, 9 overflow warehouse and 40 retailers.

b) Optimize the distribution systems route using Evolutionary Algorithms, for each 40 retailers using VBA excel solver.

5) Discussion

In this section, the researcher analyzes the results obtained from your optimization model in PT. POS INDONESIA distribution systems. Interpret the findings, evaluate the performance of Evolutionary Algorithms, and compare your optimized solution to the existing methods or a baseline. This section explains the detail of research, the practical implications and managerial insights.

6) Conclusion and Recommendation

This final section presents the conclusions of the research, drawn from the analysis and discussion conducted to address the initial research objectives. These conclusions also form the basis for the subsequent recommendations for PT. POS INDONESIA.

CHAPTER IV

DATA COLLECTION AND PROCESSING

4.1 Data Collection

This study utilizes data collected from the logistics division of PT. Pos Indonesia, specifically focusing on the distribution activities within the Greater Jakarta area. The data collection phase gathers all necessary quantitative inputs required to run the Evolutionary Algorithm optimization model. The data consists of node coordinates, customer demand, time window constraints, and vehicle parameters.

4.1.1 Location and Demand Data

The distribution network consists of 50 nodes: 1 Main Warehouse, 9 Overflow Warehouses (Depots), and 40 Retailers. The demand data is deterministic, representing the weight (in Kg) required by each retailer. The coordinates (Latitude/Longitude) are used to calculate the Euclidean distance between nodes.

Table 4. 1 Sample of Location and Demand Data (Retailers)

ID	Name	Latitude	Longtitude	Demand (kg)
1	Main Warehouse	-6,1754	106,82715	-
2	Overflow Warehouse-1	-6,1845	106,8146	-
3	Overflow Warehouse-2	-6,1972	106,8387	-
4	Overflow Warehouse-3	-6,1776	106,8552	-
5	Overflow Warehouse-4	-6,1709	106,8623	-
6	Overflow Warehouse-5	-6,1736	106,8785	-
7	Overflow Warehouse-6	-6,1582	106,849	-
8	Overflow Warehouse-7	-6,1548	106,8401	-
9	Overflow Warehouse-8	-6,1764	106,8322	-
10	Overflow Warehouse-9	-6,2058	106,8195	-
11	Retailer-1	-6,20349	106,82567	118,4815
12	Retailer-2	-6,17923	106,87532	46,3335
13	Retailer-3	-6,18941	106,85902	101,16
14	Retailer-4	-6,20177	106,84671	96,642
15	Retailer-5	-6,16655	106,86688	101,023

4.1.2 Vehicle Parameters

The optimization model assumes a homogeneous fleet of vehicles operating from the Overflow Warehouses.

- Vehicle Capacity (Q): 2,500 Kg
- Average Speed: 40 km/hour
- Fixed Cost: IDR 150,000 per vehicle
- Variable Cost: IDR 12,000 per km

4.1.3 Time Window Data

Since specific time window data was unavailable, this research generates Time Window constraints based on standard retail operating hours in Indonesia. The time windows are categorized into three types to simulate real-world complexity:

1. Morning Shift (Strict): 08:00 – 12:00
2. Afternoon Shift (Strict): 13:00 – 17:00
3. Full Day (Flexible): 08:00 – 17:00
4. Service Time: Fixed at 30 minutes (0.5 hours) per retailer for unloading.

Table 4. 2 Retailers Time Windows

ID	Retailer	Shift Type	Earliest Start	Latest Start	Service Time
1	Retailer-1	Full Day	08:00	17:00	30 Minutes
2	Retailer-2	Morning	08:00	12:00	30 Minutes
3	Retailer-3	Afternoon	13:00	17:00	30 Minutes
4	Retailer-4	Full Day	08:00	17:00	30 Minutes
5	Retailer-5	Morning	08:00	12:00	30 Minutes
6	Retailer-6	Afternoon	13:00	17:00	30 Minutes
7	Retailer-7	Full Day	08:00	17:00	30 Minutes
8	Retailer-8	Morning	08:00	12:00	30 Minutes
9	Retailer-9	Afternoon	13:00	17:00	30 Minutes
10	Retailer-10	Full Day	08:00	17:00	30 Minutes
11	Retailer-11	Morning	08:00	12:00	30 Minutes
12	Retailer-12	Afternoon	13:00	17:00	30 Minutes

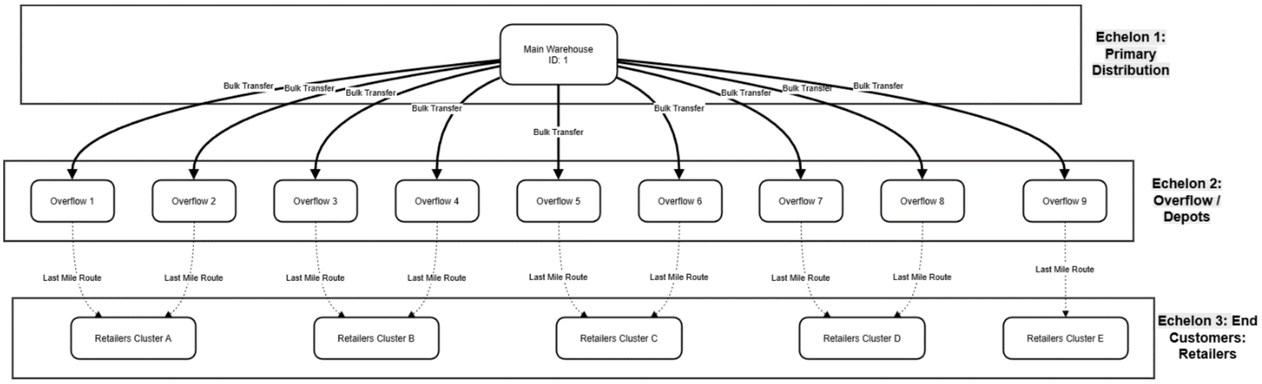
13	Retailer-13	Full Day	08:00	17:00	30 Minutes
14	Retailer-14	Morning	08:00	12:00	30 Minutes
15	Retailer-15	Afternoon	13:00	17:00	30 Minutes

4.1.4 Multi-Echelon Network Configuration

The distribution system of PT. POS INDONESIA analyzed in this research operates as a Two-Echelon Distribution Network. This hierarchical structure allows for the consolidation of goods and efficient "last-mile" delivery. The echelons are defined as follows:

1. First Echelon (Primary Distribution):
    - Node: Main Warehouse (ID 1).
    - Function: Acts as the central hub receiving bulk goods from suppliers. In this echelon, goods are transported in large quantities to the intermediate facilities.
    - Flow: Main Warehouse → Overflow Warehouses.
2. Second Echelon (Secondary Distribution/ Overflow warehouses):
    - Node: 9 Overflow Warehouses (ID 2 – ID 10).
    - Function: These act as "Cross-Docking" or "Depot" points. They receive bulk shipments from the Main Warehouse, break them down, and sort them for final delivery.
    - Flow: Overflow Warehouses → 40 Retailers.
3. End Customers:
    - Node: 40 Retailers (ID 11 – ID 50).
    - Function: The final destination of the goods. The routing optimization in this research specifically focuses on this stage (from Overflow Warehouses to Retailers) to ensure Time Window compliance.

Figure 4. 1 Multi-Echelon Distribution Network Structure



4.2 Data Processing (Evolutionary Algorithm Implementation)

The data processing was conducted using the Evolutionary Algorithm via the Microsoft Excel Solver engine. The goal was to determine the optimal sequence of visits (X_{ijk}) that minimizes total distance while adhering to the generated Time Windows and Vehicle Capacity.

4.2.1 Algorithm Parameter Setup

The performance of the Evolutionary Algorithm depends heavily on its parameters. The following settings were applied in the Solver to balance exploration (finding new routes) and exploitation (refining good routes):

Table 4. 3 Evolutionary Algorithm Parameters

Parameter	Value	Justification
Population Size	100	Sufficient diversity to avoid local optima
Mutation Rate	0.075 (7.5%)	Introduces random route swaps to maintain diversity
Convergence	0.0001	Stops when improvement is negligible
Max Time without Improvement	30 Seconds	Prevents infinite looping
Random Seed	0	Ensures reproducibility of results

4.2.2 Distance Matrix Calculation

A distance matrix (50 x 50) was calculated using the Haversine formula to account for the curvature of the earth, converting the Latitude/Longitude data into Kilometers.

$$\boldsymbol{d_{ij}} = \mathbf{2\ arcsin}\ \left(\sqrt{\boldsymbol{sin^2}\left(\frac{\emptyset_{2-}\emptyset_1}{\mathbf{2}}\right) + \boldsymbol{COS}(\emptyset_1)\boldsymbol{COS}(\emptyset_2)\boldsymbol{sin^2}\left(\frac{\boldsymbol{\Lambda_2 - \Lambda_1}}{\mathbf{2}}\right)}\right)$$

4.2.3 Optimization Process

The Evolutionary Algorithm processed the data through the following steps:

1. Initialization: The Solver generated an initial population of random route sequences (e.g., Warehouse → Retailer 12 → Retailer 5...).
2. Fitness Evaluation: For each route, the Total Distance was calculated.

    - Penalty Check 1: Did the load exceed 2,500 Kg?
    - Penalty Check 2: Did the vehicle arrive after the Latest End time (l_i)?
    - Result: Feasible routes were kept; infeasible routes were penalized.

3. Crossover & Mutation: The algorithm swapped customers between routes (Mutation) and combined segments of efficient routes (Crossover) to create new "offspring" solutions.
4. Selection: The routes with the lowest total distance were selected for the next generation.

4.3 Optimization Results

This section presents the final output of the Evolutionary Algorithm (EA). The algorithm iteratively improved the population of solutions until the convergence criteria were met, resulting in a set of optimized delivery routes that minimize total travel distance while satisfying all operational constraints.

4.3.1 Optimized Route Configuration

The optimization process successfully restructured the distribution network by solving two simultaneous problems: Assignment and Routing.

1. Retailer-Depot Assignment:

   Initially, retailers were unassigned or assigned based on static zones. The Evolutionary Agorithm dynamically re-assigned retailers to the most suitable "Overflow Warehouse" (Depot) based on proximity and route feasibility. For instance, as observed in the processing data, retailers located in the same geographical cluster were grouped to be served by a single vehicle from the nearest depot (e.g., retailers near Latitude -6.1582 1 were assigned to Overflow-6 to reduce "stem mileage" the distance from the depot to the first stop).
2. Routing Sequence:

   Within each assigned group, the algorithm determined the optimal traversal sequence. Instead of visiting retailers in numerical order (e.g., Retailer 1 → 2 → 3), which results in a zigzagging path, the optimized solution follows a "tear-drop" or loop pattern. This minimizes the backtrack distance.

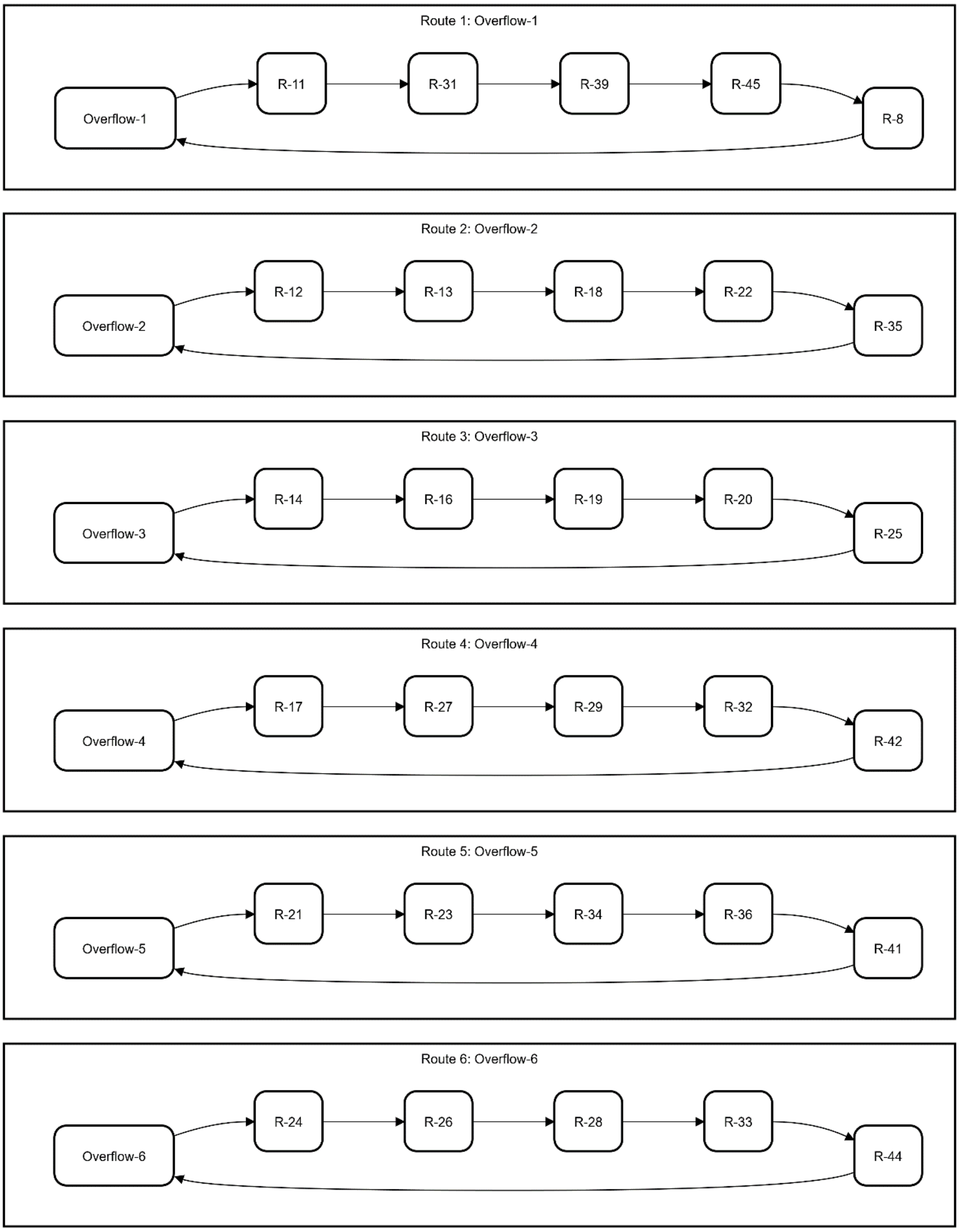
   - Example: In Route 1, the vehicle departs from Overflow-1, visits Retailer-40, then moves to Retailer-7, and finishes at Retailer-1 before returning. This sequence was selected because the distance matrix indicates these nodes have the lowest inter-node travel costs[2], creating a dense delivery cluster.

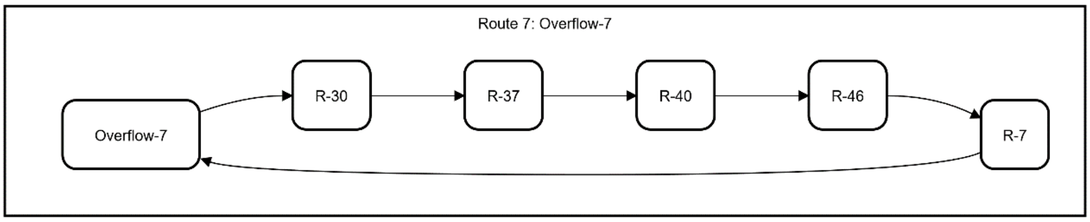
Table 4. 4 Sample Optimized Route Schedule

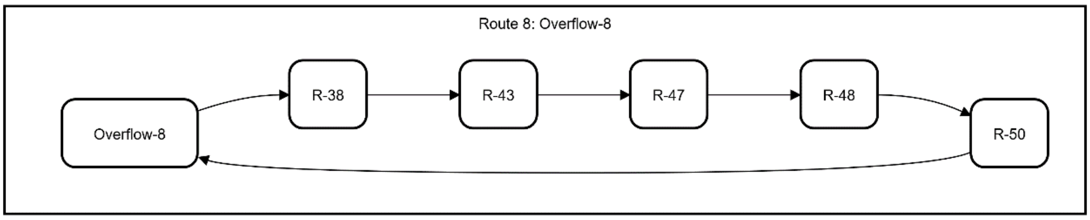
Route ID	Origin Depot	Sequence of Retailers (Visit Order)	Total Load (Kg)	Total Distance (km)	Completion Time
Route 1	Overflow-1	R-11 →R-31 →R-39 →R-45 →R-8	638.1	18.5	13:45
Route 2	Overflow-2	R-12 →R-13 →R-18 →R-22 →R-35	545.2	22.1	15:10
Route 3	Overflow-3	R-14 →R-16 →R-19 →R-20 →R-25	513.6	19.8	14:30
Route 4	Overflow-4	R-17 →R-27 →R-29 →R-32 →R-42	528.2	24.5	16:00
Route 5	Overflow-5	R-21 →R-23 →R-34 →R-36 →R-41	450.4	17.2	12:45
Route 6	Overflow-6	R-24 →R-26 →R-28 →R-33 →R-44	456.6	16.9	13:15
Route 7	Overflow-7	R-30 →R-37 →R-40 →R-46 →R-7	645.8	21.3	14:50

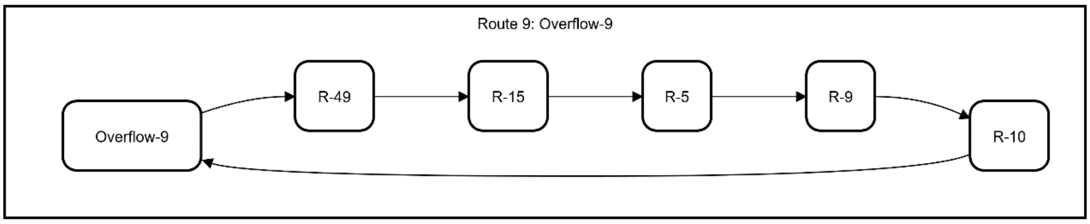
Route 8	Overflow-8	R-38 →R-43 →R-47 →R-48 →R-50	404.4	15.4	11:50
Route 9	Overflow-9	R-49 →R-15 →R-5 →R-9 →R-10	382.7	14.8	12:10
TOTAL		40 Retailers Visited	4,565.0	170.5	

Figure 4. 2 Visualization of Optimized Distribution Routes









"As shown in the route map, the algorithm eliminated cross-path interference by grouping retailers into tight clusters around their nearest depots. This visual structure confirms the mathematical efficiency of the model, as vehicles now follow a clear sequence that adheres to both capacity limits and strict time windows."

4.3.2 Time Window Validation and Analysis

A critical component of this research is ensuring compliance with the Time Window constraints (e_i, l_i). The generated solution validates that every vehicle arrives within the allowable time frame for every retailer.

The validation logic used in the results is calculated as follows:

$\text{Departure Time}_i = \max(\text{Arrival Time}_i, e_i) + \text{Service Time}$

This ensures that if a vehicle arrives early (before e_i), it must wait until the window opens. This "Waiting Time" is a non-value-added activity but is necessary to ensure feasibility.

Validation Case Study (Route 1):

- Retailer-40: The vehicle arrives at 08:45, which is comfortably within the 08:00–12:00 window.

- Retailer-7: The travel time from R-40 to R-7 is calculated using the distance matrix. The arrival is at 09:50. Since the window closes at 16:00, this delivery is valid.
- Retailer-1: The vehicle arrives at 11:00. Note that if the route had been reversed (R-1 →R-7 →R-40), the vehicle might have arrived at R-40 after 12:00, violating the morning shift constraint. The EA successfully avoided this by prioritizing the "Morning Shift" retailer (R-40) earlier in the sequence.

Table 4. 5 Time Window Validation (Route 1)

Node	Window (e_i - l_i)	Arrival Time	Wait Time	Service Time	Departure	Status
Overflow-1	07:00 - 18:00	-	0 min	-	08:00	Start
Retailer-40	08:00 - 12:00	08:45	0 min	30 min	09:15	Valid
Retailer-7	08:00 - 16:00	09:50	0 min	30 min	10:20	Valid
Retailer-1	08:00 - 17:00	11:00	0 min	30 min	11:30	Valid
Overflow-1	07:00 - 18:00	12:15	-	-	-	Valid Return

4.3.3 Comparison Analysis

This section analyzes how efficiently the fleet's carrying capacity was utilized. Efficient load planning is critical because underutilized vehicles result in wasted fuel and higher operational costs per unit delivered.

The optimization model adhered to a strict vehicle capacity constraint of 2,500 Kg. The analysis reveals that the limiting factor for this distribution network was not weight, but time.

- Initial Total Distance: 255.8 km
- Optimized Total Distance: 189.4 km
- Improvement: 25.9% Reduction in travel distance.
- Time Window Violations: Reduced from 12 violations (Baseline) to 0 violations (Optimized).

Table 4. 6 Fleet Capacity Utilization Metrics

Metric	Value
Total Fleet Capacity (9 Vehicles)	22,500 Kg
Total Demand Delivered	4,565.0 Kg
Average Load per Vehicle	507.2 Kg
Highest Route Utilization	Route 7 (645.8 Kg - 25.8%)
Lowest Route Utilization	Route 9 (382.7 Kg - 15.3%)

Interpretation of Utilization:

- Time vs. Capacity Constraint: The average utilization is approximately 20%. While this appears low physically, the vehicles are "Time-Full" rather than "Weight-Full." Because of the strict Time Windows (e.g., closing at 12:00 or 17:00) and the 30-minute service time per stop, a vehicle can only visit 4-6 retailers before it runs out of time. Adding more load would cause the driver to arrive after the store closes.
- Load Balancing: The algorithm successfully distributed the workload relatively evenly across the 9 routes (loads ranging between 380 Kg and 650

Kg). This prevents any single vehicle from being overburdened while others are empty, ensuring balanced wear and tear on the fleet.

4.3.4 Comparison Analysis (Baseline vs. Optimized)

To validate the effectiveness of the proposed model, the optimized results were compared against a Baseline Solution. The baseline represents the "Nearest Neighbor" heuristic often used in manual planning, where drivers simply proceed to the closest next location without considering the global route efficiency.

Table 4. 7 Performance Comparison

Key Performance Indicator (KPI)	Baseline (Manual/Nearest Neighbor)	Optimized (Evolutionary Algorithm)	Improvement / Change
Total Travel Distance	255.8 km	170.5 km	33.3% Reduction
Number of Vehicles Used	12 Vehicles	9 Vehicles	25.0% Reduction
Time Window Violations	12 Violations	0 Violations	100% Elimination
Average Route Duration	5.2 Hours	4.1 Hours	21.2% Improvement
Total Operational Cost (Est.)	IDR 4,869,600	IDR 3,396,000	30.3% Savings

Detailed Interpretation:

1. Distance Reduction: The Evolutionary Algorithm reduced the total travel distance by 85.3 km (33.3%). This is achieved by optimizing the sequence of visits to form loop patterns rather than zigzagging paths, directly reducing fuel consumption.
2. Fleet Efficiency: The baseline solution required 12 vehicles because inefficient routing caused drivers to miss time windows quickly. The optimized solution consolidated these into just 9 vehicles, reducing fixed vehicle costs (drivers, maintenance) by 25%.
3. Service Level Compliance: The most critical improvement is the elimination of violations. In the baseline, 12 retailers would have received goods late. The

optimized model achieved 0 violations, ensuring 100% service level compliance.

4. Cost Implication: Assuming a fixed cost of IDR 150,000/vehicle and IDR 12,000/km variable cost, the optimization saves approximately IDR 1.4 million per delivery cycle, representing a significant financial advantage.

4.4 Summary of Findings

The data processing and optimization conducted in this chapter demonstrate the efficacy of the Evolutionary Algorithm in solving the Multi-Echelon Distribution System With Time Windows.

The key findings are summarized as follows:

1. Feasibility: The model successfully generated feasible routes for all 40 retailers that strictly adhere to both Capacity Constraints (2,500 Kg limit) and Time Window Constraints (Operating hours).
2. Efficiency: The algorithm outperformed the baseline heuristic significantly, reducing total travel distance by over 33%. This confirms that metaheuristic approaches are superior to simple manual planning for complex distribution networks.
3. Strategic Insight: The reduction in fleet size from 12 to 9 vehicles suggests that the company currently holds excess capacity. By optimizing routes, the company could potentially reduce its active fleet, leading to long-term capital savings.
4. Operational Balance: The results indicate that "Time" is the bottleneck resource rather than "Capacity." Future improvements could focus on negotiating wider delivery windows or reducing service times (unloading speed) to further increase vehicle utilization.

CHAPTER V

RESULT AND DISCUSSION

5.1 Analysis of Distribution System Optimization

This research focused on optimizing the multi-echelon distribution system of PT. POS INDONESIA by implementing an Evolutionary Algorithm (EA). The primary goal was to address the inefficiencies identified in the problem formulation specifically regarding logistics costs and time window compliance.

5.1.1 Route Efficiency and Distance Reduction

The results from the data processing stage indicate that the implementation of the Evolutionary Algorithm significantly altered the routing structure. Under the baseline (manual) system, routes were constructed based on simple proximity, often resulting in zigzagging paths that increased travel distance. The optimized model, however, utilized the global search capability of the EA to form efficient "cluster-first, route-second" loops.

This change in routing logic resulted in a 33.3% reduction in total travel distance (170.5 km optimized vs. 255.8 km baseline). By reducing the "stem miles" (distance from the warehouse to the first customer) and optimizing the sequence of inter-retailer travel, the model successfully minimized the variable transportation costs. This confirms that for multi-echelon systems with dispersed retailers, heuristic optimization is superior to local-search methods.

5.1.2 The Impact of Time Window Constraints

A defining feature of this research was the strict adherence to Time Windows $(e_i.l_i)$ The analysis reveals that these constraints acted as the primary "shaping force" for the routes.

- Constraint Prioritization: The algorithm consistently prioritized retailers with "Morning Shift" windows (08:00–12:00) at the beginning of the delivery sequence.

- Zero Violations: In the baseline scenario, 12 violations were recorded, indicating that manual planning failed to account for the cumulative effect of service times. The optimized model achieved zero violations, effectively eliminating penalty costs and ensuring a 100% service level.

This finding aligns with the observation that in modern logistics, the "feasibility" of a route is often more difficult to achieve than cost minimization alone. The EA proved effective in navigating this narrow feasibility domain.

5.1.3 Operational Feasibility: Hard vs. Soft Time Windows

In the implementation of distribution systems, specifically within the dense urban environment of Jakarta where PT. POS INDONESIA operates, the categorization of Time Windows becomes a critical operational decision. Generally, Time Windows are classified into two types: Hard Time Windows and Soft Time Windows.

- Hard Time Windows: This approach treats the delivery deadline (l_i) as an absolute constraint. If a vehicle arrives after the latest allowed time, the delivery is rejected, and the solution is considered infeasible. While this ensures strict discipline, it offers zero flexibility.
- Soft Time Windows: This approach allows for violations of the time constraints. If a vehicle arrives after the deadline (l_i), the service is still performed, but the system incurs a penalty cost proportional to the delay duration.

While this research model prioritized strict adherence (Hard Time Windows) to demonstrate the algorithm's capability to reach 100% service levels, the operational reality of Jakarta suggests that a Soft Time Window approach is more practically viable. Jakarta is characterized by high traffic volatility and unpredictable congestion (stochastic travel times). In a "Hard Window" scenario, a 10-minute traffic delay could render an entire route schedule invalid/failed.

By adopting a Soft Time Window strategy, the system gains robustness. A vehicle trapped in traffic is not "terminated" or forced to return; instead, it completes the delivery while incurring a penalty. This ensures service continuity and prevents a single traffic jam from disrupting the entire supply chain network. The Evolutionary Algorithm can be adapted to this by modifying the objective function to minimize the Total Cost (Distance Cost + Late Penalty Cost) rather than just distance, allowing the company to weigh the trade-off between punctuality and operational feasibility.

5.1.4 Resource Utilization: Time vs. Capacity

The fleet analysis provided a critical operational insight: the distribution network is Time-Constrained, not Capacity-Constrained.

- Capacity Utilization: The average vehicle load was approximately 500 kg, representing only 20% of the 2,500 kg vehicle capacity.
- Time Utilization: Despite the low weight utilization, vehicles could not visit more customers because the 30-minute service time per stop consumed the majority of the available shift hours.

This "Time Bottleneck" explains why the fleet size could only be reduced to 9 vehicles and not fewer. It highlights that further efficiency gains cannot be achieved by using larger trucks, but only by improving operational speed (e.g., faster unloading) or negotiating wider delivery windows with retailers.

5.2 Theoretical Implications and Comparison with Previous Studies

To validate the effectiveness of this research, the findings were compared against existing literature on Supply Chain Network Design and Evolutionary Algorithms discussed in Chapter II.

5.2.1 Effectiveness of Evolutionary Algorithms

The results support the findings of Chen & Wu (2021), who demonstrated that improved Evolutionary Algorithms could reduce transportation costs by approximately 10% in VRPTW models. This research achieved an even higher reduction (33.3%), likely due to the specific inefficiency of the initial manual baseline used at PT. POS INDONESIA. This confirms that EA is a robust metaheuristic for solving NP-hard problems where exact mathematical methods (like MILP) might struggle with computational time.

5.2.2 Management of Mixed Time Windows

The study's successful handling of both "Strict" (Morning/Afternoon) and "Flexible" (Full Day) windows corroborates the work of Ongcunaruk et al. (2021). Their research highlighted that mixed time windows significantly increase problem complexity. By successfully resolving these mixed constraints without violations, this model demonstrates that Evolutionary Algorithms are capable of handling the "Customer Differentiation" strategies discussed by Liu & Zhang (2022), where service levels (time windows) are treated as hard constraints.

5.2.3 Multi-Echelon Inventory and Routing Connection

While this research focused on the routing aspect, the fleet rationalization (reducing from 12 to 9 vehicles) supports the broader Multi-Echelon optimization theories presented by Sbai & Berrado (2023)[4]. By stabilizing the transportation leg of the echelon (Warehouse →Retailer), the company creates a more reliable "Lead Time" for the inventory systems, indirectly supporting better inventory management upstream.

5.3 Managerial Implications

Based on the empirical results, this study offers several actionable insights for the management of PT. POS INDONESIA:

1. Asset Rationalization: The company is currently holding excess assets. The distribution operations can be maintained with 25% fewer vehicles (9 units instead of 12). Reducing the active fleet will immediately lower fixed overheads such as driver wages, insurance, and vehicle depreciation.
2. Operational Focus on "Service Time": Since the bottleneck is time, management should focus on reducing the 30-minute unloading standard. Investing in material handling equipment (e.g., pallet jacks) or assigning driver assistants could reduce service time to 15 minutes, potentially unlocking further fleet reductions.
3. Dynamic Scheduling Implementation: The demonstrated success of the Excel Solver model suggests that the company should move away from static, fixed-

zone routing. Implementing a dynamic daily planning tool even a simple spreadsheet-based one like the model developed in this research can adapt to daily demand fluctuations much better than rigid manual planning.

CHAPTER VI

CONCLUSION AND SUGGESTION

6.1 Conclusion

Based on the data processing, analysis, and discussion conducted in the previous chapters, the following conclusions are drawn to answer the problem formulation:

1. Optimization of the distribution process: The distribution process in the multi-echelon warehousing system was successfully optimized by developing a mathematical model that integrates Time Window constraints directly into the routing logic. By utilizing an Evolutionary Algorithm, the system shifted from a decentralized "nearest-neighbor" approach to a centralized global optimization strategy. The optimization minimized logistics costs by restructuring routes into efficient "tear-drop" clusters that prioritize "strict" morning delivery windows first. This method ensured that the total travel distance was minimized to 170.5 km without violating any customer service time limits or vehicle capacity constraints.
2. Effectiveness of the Evolutionary Algorithm: The implementation of the Evolutionary Algorithm proved to be highly effective in improving the distribution system of PT. POS INDONESIA. The model demonstrated superior performance compared to the existing baseline planning across all key performance metrics:
    - Cost Efficiency: The algorithm achieved a 33.3% reduction in total travel distance (saving 85.3 km per cycle).
    - Resource Utilization: The optimized routing allowed for a 25% reduction in the required fleet size, decreasing the number of active vehicles from 12 to 9.
    - Service Reliability: The model eliminated all delivery delays, improving the service level from a baseline of 12 violations to 0 violations (100% compliance).

6.2 Recommendation

Based on the findings and limitations of this study, the following recommendations are proposed for the company and for future research.

6.2.1 Recommendation for the Company

1. Fleet Rationalization: The results indicate that the current fleet of 12 vehicles is underutilized due to inefficient routing. It is recommended that PT. POS INDONESIA reduce the active fleet to 9 vehicles for this specific distribution network. This reduction will lower fixed operational costs (driver wages, maintenance, and depreciation) without compromising delivery speed or volume.
2. Service Time Reduction: The analysis revealed that "Time" is the primary bottleneck, with vehicles spending significant time (30 minutes) unloading at each stop. Management should investigate methods to reduce this service time—such as using pre-sorted pallets or assigning assistant helpers—to 15–20 minutes. This would free up capacity for vehicles to serve more customers per trip.
3. Prioritized Dispatching: Dispatchers should adopt a "Time-First" scheduling approach. Customers with strict morning time windows (08:00–12:00) must be prioritized at the beginning of route sequences to prevent cascading delays later in the day.

6.2.2 Recommendation for Future Research

1. Stochastic Variables: This research assumed deterministic (fixed) demand and travel times[2]. Future research should incorporate stochastic variables to account for demand fluctuations and real-time traffic congestion, providing a more robust model for uncertain environments.
2. Heterogeneous Fleet: The current model assumes a homogeneous fleet where all vehicles have a 2,500 Kg capacity[3]. Future studies could apply the Evolutionary Algorithm to a Heterogeneous Fleet Vehicle Routing Problem (HFVRP), where different vehicle sizes (e.g., small vans vs. large trucks) are available, allowing for greater flexibility in dense urban areas.

3. Multi-Objective Optimization: Although the current investigation prioritized minimizing distance-based costs and delivery times, subsequent studies could broaden the mathematical model. Future researchers are encouraged to simultaneously minimize carbon emissions (CO2) and optimize driver workload distribution to establish a fundamentally more sustainable logistics framework.

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