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Application of CVRP Using a Genetic Algorithm Approach to Optimize Last-Mile Delivery Costs (Case Study at the PT Pos Indonesia)

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Abstract

The logistics industry is currently grappling with substantial challenges, primarily due to intensifying price competition, a phenomenon that is being predominantly Fueled by the continuous expansion of the e-commerce sector. It has been determined that delivery costs for Last Mile Delivery (LMD) activities can account for between 28 and 60 per cent of total logistics costs, thus indicating that this area is of critical importance with regard to optimization. PT Pos Indonesia is confronted with a significant challenge in preserving price competitiveness within this evolving market. The objective of this study is to make a comparison between the costs of LMD operations in two different models. The initial strategy entails the externalization of operations, wherein a success-based fee is levied for each completed package. The second strategy involves the implementation of an in-house model, where transportation vehicles and human resources are managed internally, in conjunction with route optimization utilizing CVRP. The present study employs a research methodology that entails the calculation of the cost per package for both models. This calculation encompasses CAPEX, OPEX and potential operation uncertainties risks. This study's findings indicate the viability of implementing the in-house operational model to achieve a reduction in monthly expenses of up to 7.11% (Rp. 1,920,162). Furthermore, the application of CVRP in conjunction with the Genetic Algorithm method has been shown to result in significant savings, including a reduction in travel distance by 142.6 km and an improvement in delivery time by 381 minutes when compared to the outsourcing operational model. It is anticipated that the study will furnish PT Pos Indonesia with strategic recommendations for the

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determination of the most optimal operational model for LMD activities, with a view to enhancing the company's efficiency and competitiveness in the future.

Keywords: Last Mile Delivery; Outsourcing vs. In-house; Clusters; CVRP; Clarke and Wright Savings; Genetic Algorithm.

INTRODUCTION

Transportation and distribution are two fundamental components of logistics activities, and their integration is paramount to the overall effectiveness of the logistics ecosystem. Transportation is a critical component of the distribution of goods and services. However, these activities do not add value to the product but rather tend to incur costs. Factors such as delivery time, cargo weight, and distance traveled influence transportation costs; the higher these three factors are, the greater the costs incurred (Ferdiansyah et al., 2024).

Logistics costs are one of the factors that most significantly influence a company's competitiveness (Sains et al., 2022). Analyzing various factors within a business is a crucial step for companies, particularly in efforts to optimize operations comprehensively. It is hypothesized that the results of this study will provide practitioners and decision-makers with useful insights, and researchers in addressing existing challenges and improving distribution cost efficiency in business activities (Budiman, 2025).

In the contemporary business environment, achieving cost efficiency is imperative to maintain logistics companies' competitiveness in today's global economy (Mogale et al., 2025). Moreover, there has been a substantial expansion in the online shopping sector, especially in the aftermath of the pandemic. This has resulted in a considerable surge in both shipment volumes and the intricacy of supply chain logistics processes (Escudero-Santana et al., 2022). In addition, as (Lestiani et al., 2021) explain, achieving a competitive advantage is imperative for companies to compete and successfully advance.

Within the domain of supply chain management, a final stage is referred to as the last-mile delivery (LMD), which occurs when products are transported from a distribution facility directly to a customer's location. This process is recognized as the least economical and most complex element of supply chains. As demonstrated by (Badrinarayanan, 2024), the financial implications of LMD can account for between 28 and 60 percent of aggregate shipping expenses. This predicament poses a substantial obstacle to logistics enterprises, as the incapacity to enhance and systematize this procedure can diminish cost efficiency in the industry (Purnomo et al., 2023). The

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challenges associated with the last-mile delivery phase (LMD) encompass time constraints, travel duration, the quantity of couriers, the efficacy of deliveries, and elevated operational expenses, particularly within urban contexts.

PT Pos Indonesia, the focal point of this inquiry, is a corporation that specializes in courier and logistics services. The enterprise provides a range of services, including logistics and transportation, as well as warehousing, to various regions within Indonesia. However, the company is currently confronted with a series of challenges in the face of rapidly expanding electronic commercial activity. These challenges are attributable not just to an expanding number of competitors but also to intensifying price competition, as illustrated in Table 1 below.

Table 1. Rate Comparison

No	Origin	Destination	Pos	JNE	J&T	Sap	Tiki	IDX
1	Pekanbaru	Medan	23,000	23,000	22,000	24,000	20,000	21,600
2	Jambi	Medan	40,500	41,000	30,000	38,000	25,000	35,100
3	Palembang	Medan	32,000	44,000	32,000	36,000	34,000	34,100
4	Bengkulu	Medan	36,000	62,000	36,000	42,000	43,000	39,100
5	Bandarlampung	Medan	41,500	49,000	34,000	37,000	34,000	35,100
6	Aceh	Medan	29,000	29,000	29,000	28,000	33,000	-
7	Batam	Medan	34,000	36,000	38,000	36,000	36,000	32,100
8	Padang	Medan	21,000	23,000	22,000	20,000	19,000	20,600
9	Medan	Medan	7,000	5,000	7,000	8,000	6,000	7,100
10	Jakarta	Medan	37,000	47,000	36,000	37,000	39,000	36,100

As demonstrated in Table 1, PT Pos Indonesia has confronted difficulties in sustaining competitive rates in comparison to its competitors on multiple sampled routes. This challenge is also evident in the restricted range of PT Pos Indonesia's services available on major e-commerce platforms. The observed phenomenon can be attributed to the propensity of sellers to prioritize shipment by companies that can offer the most economical rates. This strategic decision is made with the primary objective of maintaining buyer satisfaction, as buyers inherently seek reduced shipping costs, expedited delivery times, and assured package security.

Based on these real-world observations, customers will think twice before using PT Pos Indonesia’s services. This will impact the market share that PT Pos Indonesia is able to capture in both the electronic commerce and non-electronic commerce sectors, as shown in Table 2 below.

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Table 2. Share of Market

Organization	% Share of Market
J&T	51,5%
JNE	11,4%
Tiki	11,6%
Pos Indonesia	4,1%
Others	21,4%

As illustrated in Table 2 above, PT Pos Indonesia's market share is a mere 4.1%. Should this situation persist over an extended period, PT Pos Indonesia may experience further delays in catching up with its competitors in the courier and logistics industry, which is becoming increasingly competitive. Consequently, in order to maintain and enhance its competitiveness, PT Pos Indonesia must focus on the domain with the most significant potential for enhancing efficiency while concurrently providing added value to customers: the Last Mile Delivery (LMD) process.

Presently, PT Pos Indonesia is implementing an outsourcing model for its LMD processes across multiple operational regions. In accordance with the provisions stipulated within the framework of the aforementioned program, outsourcing partners receive a remuneration amount calculated on the basis of the number of successfully delivered packages. Furthermore, supplementary bonuses are distributed in alignment with the stipulated terms and conditions. The "successfully delivery" indicator signifies the receipt of the package by the intended recipient, a fact that has been meticulously documented within the enterprise's system. An analysis of the extant data suggests that the mean costs associated with successfully delivering a package via the outsourcing partners at PT Pos Indonesia's Medan Kota Distribution Centre (DC) range between 28% and 40% of the overall total shipping costs. Consequently, the enhanced efficiency of PT Pos Indonesia's LMD process may enable the company to engage in competitive pricing with its existing competitors.

In view of the foregoing, the problem addressed in this study is the challenge faced by PT Pos Indonesia in the face of the rapid growth of e-commerce. This study hypothesizes that the growth of e-commerce will be proportionate to an increased necessity for package transportation services. Nonetheless, it is evident that this growth has not been accompanied by a corresponding rise in demand for PT Pos Indonesia's services. This phenomenon can be attributed to the company's limited service portfolio within the e-commerce sector, which is compounded by the

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intense price competition that characterizes the logistics industry.

This study aims to provide a comprehensive cost comparison of LMD activities by assessing the relative merits of outsourcing and in-house operational models. This analysis will be further augmented by the application of the CVRP. The CVRP combination is predicted to enhance delivery route optimization and minimize the number of couriers. Consequently, PT Pos Indonesia is poised to reduce operating costs, augment efficiency, and uphold its market competitiveness.

In this study, the following steps are to be taken:

1. Calculating LMD costs using the outsourcing operational model.
2. Calculating LMD costs using an in-house model, which includes Capital Expenditure (CAPEX), Operational Expenditure (OPEX) and Potential Adverse Effects and Associated Hazards.
3. Determining delivery zones using the K-Means clustering method and the number of delivery personnel for each zone.
4. Conducting simulations of the impact of CVRP efficiency using the Clarke and Wright saving method and the genetic algorithm on in-house LMD costs.
5. Determining the most optimal method for selecting an LMD strategy.

Once this LMD strategy's most optimal method has been identified, this analysis will serve as the foundation for recommending revisions of PT Pos Indonesia's current policies, should more efficient and profitable methods be identified.

LITERATURE REVIEW

In recent years, a number of studies have examined initiatives aimed at enhancing the efficiency of LMD. A recent study (Elvas et al., 2023) posits that supply chain companies must seek tech-based strategies to enhance LMD effectiveness. The conception of intelligent systems is predicated on a vast accumulation of data, colloquially referred to as "Big Data." The substantial volume of available data in this context facilitates predictions of a given subject's prospective behaviors in light of previous observations.

A recently published study by (Loan et al., 2022) examined the manner in which supply chain enterprises are implementing unsupervised models for delivery, including Crowd Delivery Platforms (CDPs) and Parcel Lockers (PLs). These models have emerged as a pivotal trend in minimizing operational expenses for delivery service providers, thereby playing a pivotal role in the efficacy of the business-to-consumer (B2C) distribution system. Additionally, a study by (Nazari et al., 2018) puts forward a novel approach that utilizes the technique of reinforcement learning to address the computationally demanding VRP.

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A recent study (Badrinarayanan, 2024) demonstrated that the combination of two technologies, called AI and ML, has significantly impacted the operations of LMD, which is recognized as e-commerce logistics' most challenging and costly segment. Concurrently, a research study (Oloko, 2025) examined the implementation of machine-learning algorithms as an effective solution to optimize last-mile shipping pathways in real time. The study employed machine learning methodologies, incorporating both decision trees and neural networks that were previously trained on a historical dataset.

A recent study (Kumar Paul & Sarkar, 2021) proposed a novel machine learning method tailored for location-based LMD forecasting. The objective of the study was twofold: first, to minimize operational expenditures; and second, to enhance overall efficiency within two sectors, i.e., the supply chain and e-commerce. Moreover, a recent study (Pal, 2023) proposes that integrating machine learning with data and sophisticated algorithms can proactively enhance logistics decision-making based on data. The methodology under consideration is designed to proactively anticipate challenges, dynamically adjust routes, and ensure the seamless operation of logistics.

A study by (Sekhar Veluru, 2023) presents a novel framework that utilizes Generative Artificial Intelligence, also known as Gen AI, for the optimization of distribution networks. This framework utilizes both real-time traffic data and environmental conditions to facilitate optimal decision-making processes concerning route planning. The primary aim of these initiatives is to ascertain optimal routes, with the objective of achieving a substantial reduction in operational expenditures while concomitantly enhancing the precision and expediency of deliveries. This approach entails a dynamic adaptation to fluctuating traffic and meteorological conditions. Concurrently, a case-based modeling approach is employed in a study (Mogale et al., 2025) in order to address a Multidepot VRP encountered by a prominent UK retail company, Alpha Partnership Network (APN), as it expands its operations in the northern region of the country.

As a consequence of the aforementioned discussion, the researchers identified a research gap in the extant literature, specifically the absence of comparative cost analyses between operational models that are outsourced and in-house, in conjunction with the application of the CVRP. The CVRP methodologies to be employed are the Clarke and Wright savings method and the genetic algorithm. This study is confined to the operational domain of PT Pos Indonesia's Medan Kota Distribution Center (DC).

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METHOD

Research Methodology

In this study utilizes of quantitative approach, employing a meticulous examination of numerical data, encompassing cost estimations, route optimizations via the CVRP, and the process of data validation is achieved through the use of triangulation. The use of a quantitative approach is substantiated by a series of mathematically derived formulations. These formulations encompass calculations of the following: the cost per package, the total operational costs, and the asset depreciation. Data collection was conducted through observation and review of documents available at PT Pos Indonesia.

The data presented herein were collected through direct observation and in-depth interviews with managerial and operational personnel at PT Pos Indonesia Medan Kota Distribution Center (DC).

1. The vehicles used for customer deliveries are motorcycles with engine capacities ranging from 125 to 150 cc.
2. The average vehicle capacity per trip is 40 packages, and the number of daily delivery trips is 3.
3. Data on the workload and productivity of delivery partners, including travel time, the number of shipments each route, and effective operational hours.

The data set presented herein was obtained by means of a comprehensive review of corporate records, including financial documents, as well as from ancillary data resources, such as the logistics sector's periodicals and cartographic resources. The following data has been collected:

1. The number of active partners that have been outsourced, in addition to the monthly financial obligations associated with each partner.
2. Average volume of successful deliveries per month is measured.
3. Average LMD operating costs using the outsourcing method, derived from partner payment reports for the past six months.
4. Addresses of the 22 neighbourhoods in the delivery area served by the Medan Kota Distribution Center (DC).
5. Geographic coordinates (latitude and longitude) of the 22 neighbourhoods in the delivery area served by the Medan Kota Distribution Center (DC), obtained from Google Maps.
6. Data on the distances between regions, calculated using road distances (km), was obtained from Google Maps.

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The fundamental metric employed for determining the distribution load per area is the average daily package volume per substate.

Last Mile Delivery (LMD)

The concluding phase of a distribution process is designated as last-mile delivery. This stage is characterized as the culminating phase in the process of logistics, wherein the goods are delivered to the consumer directly. Logistics professionals recognize LMD as a complex procedure due to its inherent unpredictability (Elvas et al., 2023). Furthermore, (Milisavljevic & Vasić, 2024) posit that the Last-Mile Delivery (LMD) phase signifies a culminating phase of a transport process, particularly with regard to the delivery from a distributor to an end consumer. Notwithstanding its status as a component of the supply chain that is both final and least extensive, LMD is distinguished by its elevated cost, which frequently accounts for up to 50% of total logistics expenditures, and its intricate nature in terms of execution. The efficacy of a company's customer experience strategy has been demonstrated to exert a substantial influence on customer satisfaction and loyalty. Consequently, this strategy functions as a catalyst for competitive advantage. The term “LMD” has become increasingly popular over the past decade alongside the rapid development of the internet and online shopping. More and more consumers are ordering products online and expect a simple ordering system, transparency and package traceability, fast and affordable home delivery, and undamaged products. The rapid growth of e-commerce and the COVID-19 global health crisis have driven consumers to switch to online shopping, leading to a remarkable increase in e-commerce sales and mounting pressure on last-mile logistics.

Logistic Cost Analysis

The process of logistics cost analysis is characterized as the identification, measurement, and evaluation of the cost components that arise in logistics activities (Syahraul et al., 2024). These activities include, but are not limited to, transportation, warehousing, packaging, inventory management, and distribution. In the context of the logistics economy, this analysis plays a crucial role because logistics cost efficiency directly impacts competitiveness and economic stability, both at the corporate and national levels. High logistics costs can increase product prices, reduce profit margins, and hinder the flow of goods, whereas logistics efficiency can reduce production costs, accelerate inventory turnover, and drive economic growth through increased productivity and more optimal supply chain integration.

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Outsourcing vs. in-house

Outsourcing can be defined as the practice of delegating specific tasks to external entities that possess the necessary expertise in a particular field, with the objective of reducing costs and enhancing efficiency. Conversely, the term "in-house" refers to the allocation of all tasks, including the provision of equipment, to the company's internal team (Panjaitan B, 2016). The practice of outsourcing has been demonstrated to offer certain advantages, including enhanced efficiency in terms on timing, reduction in costs, as well as facilitated and expedited access to skilled labor, obviating the necessity of a protracted recruitment process. Nevertheless, it is imperative to acknowledge that outsourcing is not without its inherent risks. These include the potential for diminished control, the emergence of quality issues, and elevated levels of employee turnover. The following components comprise the cost elements of outsourcing:

1. The financial remuneration for each successfully delivered package,
2. Bonus calculations for each successfully delivered package,
3. Operational risks borne entirely by the partner (zero cost to the company).

To calculate the cost of the outsourcing model, one must first determine the appropriate formula.

$$\text{Unit Cost}_{\text{outs}} = \frac{\text{Total Partner Payment Costs}}{\text{Total Packages Succesfully Delivered}} \quad (1)$$

Where:

a) Total Partner Payment Costs is the mean aggregate payment made to all external courier services, including bonuses, within a given month.
b) Total Packages Succesfully Deliveredis the average total number of packages successfully delivered (successful delivery status).

Conversely, the in-house model affords comprehensive oversight of work processes, quality assurance, and data confidentiality. However, it generally necessitates higher operating costs due to its inclusion of personnel expenses, training, and facilities. The following components comprise the in-house cost elements under consideration in this study:

1. CAPEX (Capital Expenditures) covering motorcycles, helmets, delivery boxes, safety equipment, and courier uniforms.
2. OPEX (Operating Expenses) includes couriers' base salaries for couriers, as well as allowances for couriers, insurance for couriers, fuel for vehicles, vehicle taxes, and maintenance costs of vehicles.

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The following formula is employed to calculate the in-house model cost:

$$\text{Final Cost}_{\text{inhouse}} = \text{Capital Expenditure Depreciation} + \text{OPEX} \quad (2)$$

$$\text{Final Unit Cost}_{\text{inhouse}} = \frac{\text{Total Monthly Cost}}{\text{Total Parcels every Month}} \quad (3)$$

$$\text{Final Annual Depreciation} = \frac{\text{Acquisition Cost} - \text{Residual Value}}{\text{Economic Age}} \quad (4)$$

$$\text{Final Monthly Cost Depreciation} = \frac{\text{Annual Depreciation}}{12} \quad (5)$$

Where:

a) CAPEX Depreciation is the depreciation of investment costs for assets.
b) OPEX represents all operating costs for running operation in-house model.
c) Total Monthly Cost is the aggregate of all operation in-house costs in a month.
d) Total Parcels every Month is the total of packages success distributed each month.
e) Acquisition Cost is the purchase cost for the investment asset.
f) Residual Value is defined as the remaining economic value of an asset following the conclusion of its designated economic life
g) Economic Age is the asset's useful life (in years).

Subsequently, the cost calculations for both models will be amalgamated to calculate savings and determine the optimal one. The calculation of the comparative expense between outsourcing and in-house models can be determined by utilizing the formula provided below.

$$\text{Unit Costs Comparison Index} = \frac{\text{Unit Cost}_{\text{outs}}}{\text{Unit Cost}_{\text{inhouse}}} \quad (6)$$

$$\text{Unit Savings \%} = \frac{\text{Unit Cost}_{\text{outs}} - \text{Unit Cost}_{\text{inhouse}}}{\text{Unit Cost}_{\text{outs}}} \times 100\ \% \quad (7)$$

$$\text{Unit Saving} = \text{Unit Cost}_{\text{outs}} - \text{Unit Cost}_{\text{inhouse}} \quad (8)$$

$$\text{Monthly Saving} = \text{Unit Saving} \times 30 \quad (9)$$

Clustering

Clustering is a method in statistics used to group or separate data into specific clusters based on existing characteristics (Azizah et al., 2022). One of the most commonly used methods in cluster

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analysis is K-Means; this method is capable of grouping or separating data into homogeneous clusters based on relevant characteristics, typically for numerical data, using a grouping scheme based on distance (Triyaningsih, 2023). Prior to executing the CVRP, the K-Means clustering method was implemented for the purpose of categorizing service areas on the basis of geographic proximity as well as their respective regional attributes. These objectives include reducing the complexity of the VRP, dividing the service areas more evenly, and generating more realistic routes.

The objective of clustering is to decompose the problem. To that end, the K-Means algorithm is employed to cluster delivery areas according to geographic proximities. This approach enables the division of the service area in a more efficient and structured manner. The process is initiated with the determination of the number of clusters that will provide the best possible fit. This method, termed the "Elbow Method" (EM), is a data mining approach entailing the calculation of various WCSS values for different integer values of k. Subsequent to this calculation, the EM identifies the "elbow" point on the WCSS-k plot, which corresponds to a substantial change in the data. The WCSS formula employed is

$$\mathrm{WCSS}(k) = \sum_{j=1}^{k} \sum_{x_i \in c_j} \| x_i - \mu_j \|^2 \qquad (10)$$

In this context x_i denotes a specific location or point of interest under consideration, μ_j signifies the center of the jth cluster, and c_j signifies the set of data points falling inside that particular cluster. This method fosters a more uniform segmentation of domains, thereby facilitating the optimization of routes, workloads, and resource requirements with greater efficacy.

Vehicle Routing Problem (VRP)

In distribution systems, VRP stands as a critical issue with the objective of identifying the most efficient routes for a set of vehicles with specific capacities (Putra Wijaya & Kusdanu Waskito, 2025). The objective is to fulfill all customer requests in an optimal manner, taking into account the locations and quantities of requests that are known in advance. An optimal route is defined as one that meets various operational constraints, minimizes total distance and travel time while serving customer requests, and effectively utilizes a limited number of vehicles (Ferdiansyah et al., 2024).

Additionally, the study proposes an integrated framework capable of addressing the vehicle

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routing problem from start to finish. The VRP is a combinatorial optimization problem that is computationally very difficult and has been the subject of research for decades (Chandra & Setiawan, 2018). The primary goal of such research has been to optimize a set of routes to achieve maximum reward. This is often achieved by minimizing total distance or service time, which ultimately minimizes costs (Hajar et al., 2024).

In the context of the Vehicle Routing Problem, several assumptions are made. The following assumptions were made: each vehicle is assumed to have an equal capacity, the total number of vehicles is assumed to be unlimited, demand for service at each node is known, and no single demand exceeds the vehicle's capacity (Sugiono, 2022). While the theoretical framework assumes an unlimited number of vehicles, this study imposes a limit on the number of vehicles based on real-world conditions at the company.

Capacitated Vehicle Routing Problem (CVRP)

The CVRP model is distinct from the VRP model in that it emphasizes the optimization of routes for product distribution, taking into account the capacity of vehicles. The primary objective is to optimize the reduction of both the total distance covered and the distribution cost, while adhering to the constraints imposed by the load capacity limit (Kristina et al., 2021). The evaluation of such systems is typically performed using an objective function that measures the effectiveness of the result. Examples of the aforementioned functions include total distance traveled, total transportation cost, the quantity utilized of vehicles, and the combination of said elements. In subsequent phases, the outputs of the solution will be evaluated in relation to optimal and benchmark values. This evaluation is performed by employing a suite of optimization algorithms. These include exact methods, such as branch-and-bound, heuristics, including the savings algorithm and the nearest neighbor, as well as metaheuristics, such as the genetic algorithm, tabu search, and ant colony optimizer. To that end, the following mathematic formulation is employed:

$$\min \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij} \qquad (11)$$

Where:

a) c_{ij} is defined as the interval between nodes i and j.
b) x_{ij} is assigned a value of 1 if the route is selected and 0 if it is not selected.

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Clarke and Wright's Saving (CWS) Heuristic Method

CWS Algorithm is a heuristic algorithm that was developed for the purpose of solving the VRP. This approach is predicated on the concept of savings, which involves calculating the efficiency gains achieved when two customers are combined into a single route (Purnomo et al., 2023). In the initial phase, it is hypothesized that each customer is served by a distinct route. Subsequently, the routes between customers i and j are amalgamated, with the resulting distance savings being taken into account. These savings are calculated using the formula `$s_{ij} = c_{io} + c_{oj} - c_{ij}$`, where `$c_{ij}$` means the distance between customer i to customer j. This approach has been widely used because it is simple and effective in producing near-optimal solutions.

In the context of CVRP, the Clarke and Wright Saving method is implemented through a series of procedural phases.

1. The preliminary solution consists of discrete routes, with each customer being attended to by a single vehicle. The initial route is defined as follows: $0 \rightarrow i \rightarrow 0$ where i denotes the customer in question.
2. The "savings" value for each customer pair must be calculated using the following formula:

$$s_{ij} = d_{i0} + d_{0j} - d_{ij} \quad (12)$$

As the magnitude of the savings value increases, the greater the advantage of consolidating the two customers into a unified route.
3. The third step in the process is the sorting of all customer pairs from highest to lowest savings value. This is referred to as "greedy sorting." The fundamental economic principle underpinning this approach is to prioritize the selection of the combination that generates the most substantial savings.
4. The fourth step involves verifying the alignment of two proposed routes with vehicle capacity constraints. In instances where the aggregate demand for the two routes is less than the vehicle capacity Q, the combination is permitted.
5. The two routes should be amalgamated into a single new route, with the following structure: The sequence $0 \rightarrow \cdots \rightarrow i \rightarrow j \rightarrow \cdots \rightarrow 0$ is repeated, contingent upon its execution in the order of the most substantial viable reductions.
6. It is imperative to reiterate the merging procedure until the subsequent condition is fulfilled:
   a) It has been determined that there are no longer any customer pairs with valid savings.
   b) It has been determined that all potential pathways have been consolidated within the established capacity limit.

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7. The result of this process is a final route that is more optimal than the initial individual solutions, because the latter merely maximize the sum total distance reductions. The subsequent figure delineates the steps for solving the Clarke and Wright Savings CVRP method.



Fig 1. Flowchart of the solution steps for the CWS CVRP method

Genetic Algorithm Metaheuristic Method

The Genetic Algorithm method is one of the methods used to solve optimization problems, including determining the shortest route. The computational mechanism of this algorithm mimics the process of natural selection among living organisms within a population. Therefore, the solution search process in the genetic algorithm is performed in parallel by evaluating multiple candidate solutions simultaneously, thereby enabling the attainment of more optimal solutions (Isai & Nugroho, 2024).

Genetic Algorithms work by mimicking the mechanisms of natural evolution. In the evolutionary process, individuals with better adaptive abilities will survive and thrive, while those with lesser abilities will be eliminated. This concept is applied in genetic algorithms to find the best solutions within a population. This evolutionary process commences in a state of random genetic variation, wherein each chromosome is endowed with a distinct set of genes. Subsequently, through the processes of selection, mutation, and recombination, increasingly better individuals are produced from one generation to the next until a solution that approaches

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or reaches the optimal is finally obtained (Rahimi et al., 2023).

A genetic algorithm is generally considered to have reached convergence when approximately 80% to 85% of the chromosomes in the population have the same or very similar gene values. To prevent premature convergence, it is important to maintain a level of diversity within the population. In genetic algorithms, this diversity can be maintained through the use of operators such as crossover and mutation, which play a role in generating new variations in the chromosomes so that the solution search process remains exploratory. According to Haupt and Haupi (cited in (Isai & Nugroho, 2024)), the basic structure of a genetic algorithm consists of the following steps:

1. Population Initialization Process

An initial population of size N is generated randomly. This population is represented as a set of chromosomes, namely [K1, K2, ..., KN].

2. Population Evaluation Process

Each individual in the population is evaluated using the fitness function, f(Ki). This fitness value is used to measure how well the chromosome approaches or achieves the expected solution. The formula used to calculate the fitness value is as follows:

$$\text{Fitness} = \frac{1}{(\text{fx})} \tag{13}$$

Where:

$$\text{fx} = \Sigma(\alpha D_{ij}) + \Sigma(\alpha P) \tag{14}$$

Where:

a) D_{ij} is defined as the distance from point i to point j.
b) P is the penalty amount that will be assessed if the customer is served outside of the established schedule. It is imperative to refrain from utilizing bullet points in this context.

3. Selection Process

Some of the best chromosomes in the current population are selected to form the next generation. This selection process can be based on the fitness value of each individual or using a probabilistic selection approach.

4. Crossover Process

Crossover is one of the operators in a Genetic Algorithm that combines two parents to produce offspring chromosomes. In this stage, specific pairs of chromosomes are selected to undergo the crossover process, which involves the exchange of genetic material between them to form new chromosomes as a result of the combination.

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5. The Mutation Process

After undergoing the crossover process, the resulting chromosomes (offspring) may undergo mutation. Mutation is performed by altering one or more genes in an individual; however, not all crossover results will be mutated, as the number depends on the predetermined mutation probability. In Genetic Algorithms, mutation serves to restore genes that may have been lost during the selection process and to introduce new variations not present in the initial population. Thus, mutation helps increase population diversity. At this stage, specific chromosomes are selected to undergo random changes in their constituent genes. The type of mutation used is swap mutation, which involves randomly selecting two genes and then swapping their positions or values with one another.

6. Evaluation of the New Population

After the crossover and mutation processes are complete, a new population is formed. At this stage, the quality of the resulting solutions is assessed by re-evaluating all individuals in the population using the fitness function.

7. Repeat from step 3

Steps 3 through 6 are repeated until the termination condition is met. The termination condition may be reaching the optimal solution, reaching a certain iteration limit, or other termination conditions. The steps for solving the CVRP GA are presented in the figure below.

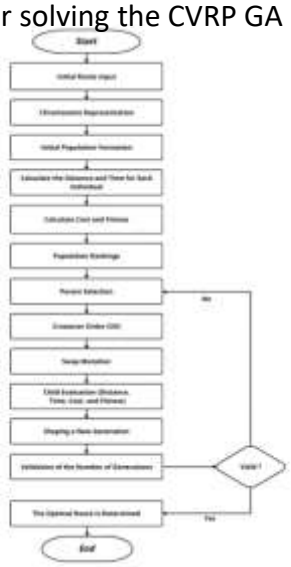


Fig 2. Flowchart of the steps for solving the CVRP GA method

Furthermore, each stage of the problem-solving process in this study is shown in the figure below.

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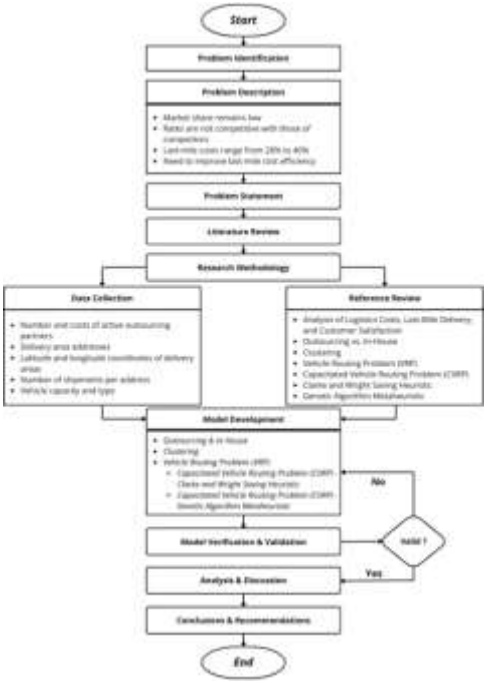


Fig 3. Flowchart of the problem-solving steps

RESULT AND DISCUSSION

Demand Distribution and Delivery Areas

The subsequent data concerning the distribution of demand and delivery areas at the PT Pos Indonesia Medan Kota distribution center served as the foundation for this study.

Table 3. Demand Distribution and Delivery Areas / Day

Origin	Destination	Label	Distance (km)	Demand
Distribution Center	Kesawan Subdistrict	A1	1.5	60
	Petisah Tengah Subdistrict	A2	2.5	40
	A U R Village	A3	2.3	26
	Hamdan Subdistrict	A4	2.6	15
	Kel Anggrung	A5	4	17
	Madras Hulu Village	A6	2.7	12
	J A T I Subdistrict	A7	3.3	15
	Polonia Subdistrict	A8	5.7	19
	Sari Rejo Village	A9	7.8	20

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	Suka Damai Village	A10	5.5	14
	Kampung Baru Village	A11	5.6	19
	Sei Mati Subdistrict	A12	3.9	13
	Sukaraja Village	A13	3.3	12
	Psr Merah Barat Village	A14	3.8	13
	Psr Merah Timur Subdistrict	A15	4.7	12
	Teladan Barat Subdistrict	A16	4.5	12
	Kel Teladan Timur	A17	5.4	14
	Sudirejo I Village	A18	5.4	15
	Sudirejo II Village	A19	5.7	12
	Sitirejo I Village	A20	5.1	14
	Sitirejo II Village	A21	6.6	14
	Sitirejo III Village	A22	6.8	12
Total				**400**

The demand data previously presented in tabular form will be converted into map-based geographic visualizations. These visualizations aim to simplify and provide a clearer, more structured, and more informative overview of field conditions regarding the distribution of demand points within the study area.



Fig 4. Geographic map of delivery points

Initial Distribution Costs for LMD Points

The distribution costs incurred under the outsourcing or existing operational models to deliver goods from the distribution center to 22 LMD delivery points are as shown in the table

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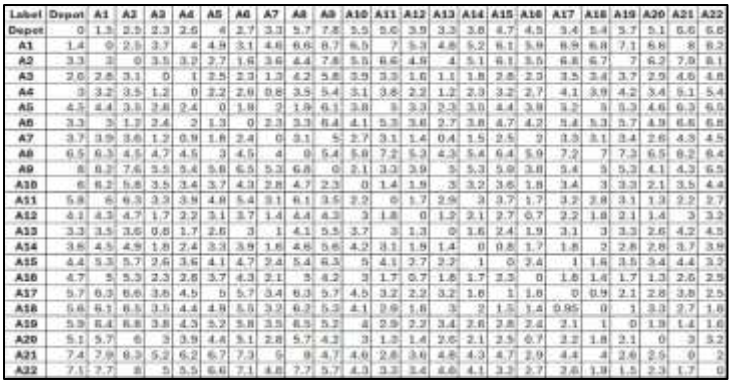
below.

Table 4. Initial Distribution Costs

Type Operation	Average Number of Packages/Month	Average Cost/Month	Average Cost per Package
Outsourcing	12,000	27,000,000	2,250

Distance and Time Matrix Data

The following presents the distance and time matrix data that will be used in the process of determining the optimal distribution route for deliveries, both in terms of distance traveled and delivery time. This matrix data contains information on distances and estimated travel times between delivery points, starting from the Distribution Center to 22 delivery areas within the operational coverage of PT Pos Indonesia Medan Kota.



Label	Depot	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21	A22
Depot	0	1.3	2.5	2.3	2.6	4	2.7	3.3	5.7	7.8	5.5	5.6	3.9	3.3	3.8	4.7	4.5	3.4	5.4	5.7	5.1	6.6	6.8
A1	1.4	0	2.5	3.7	4	4.9	3.1	4.6	6.6	8.7	6.5	7	5.3	4.8	5.2	6.1	5.9	6.9	6.8	7.1	6.6	8	8.2
A2	3.3	2	0	3.5	3.2	2.7	1.6	3.6	4.4	7.8	5.5	6.6	4.9	4	5.1	6.1	5.5	6.8	6.7	7	6.2	7.6	8.1
A3	2.6	2.8	3.1	0	1	2.5	2.3	1.3	4.2	5.8	3.9	3.3	1.6	1.1	1.8	2.8	2.3	3.5	3.4	3.7	2.9	4.6	4.8
A4	3	3.2	3.5	1.2	0	2.2	2.9	0.8	3.5	5.4	3.1	3.8	2.2	1.2	2.3	3.2	2.7	4.1	3.9	4.2	3.4	5.1	5.4
A5	4.5	4.4	3.5	2.8	2.4	0	1.8	3	1.9	6.1	3.8	3	3.3	2.3	3.0	4.4	3.8	5.2	5	5.3	4.6	6.3	6.5
A6	3.3	3	1.7	2.4	2	1.3	0	2.3	3.3	6.4	4.1	5.3	3.6	2.7	3.8	4.7	4.2	5.4	5.3	5.7	4.9	6.6	6.8
A7	3.7	3.9	3.6	1.7	0.9	1.8	2.4	0	3.1	5	2.7	3.1	1.4	0.4	1.5	2.5	2	3.5	3.1	3.4	2.6	4.3	4.5
A8	6.5	6.3	4.5	4.7	4.5	3	4.5	4	0	5.4	5.8	7.2	5.3	4.3	5.4	6.4	5.9	7.2	7	7.3	6.5	8.2	8.4
A9	8	8.2	7.6	5.5	5.4	5.8	6.5	5.3	6.8	0	2.1	3.3	3.9	5	5.3	5.9	3.8	5.4	5	5.3	4.1	4.3	6.5
A10	6	6.2	5.8	3.5	3.4	3.7	4.3	2.8	4.7	2.3	0	1.4	1.9	3	3.2	3.6	1.8	3.4	3	3.3	2.1	3.5	4.4
A11	5.9	6	6.3	3.3	3.9	4.9	5.4	3.1	6.1	3.5	2.2	0	1.7	2.9	3	3.7	1.7	3.2	2.8	3.1	1.3	2.2	2.7
A12	4.1	4.3	4.7	1.7	2.2	3.1	3.7	1.4	4.4	4.3	3	1.8	0	1.2	2.1	2.7	0.7	2.2	1.8	2.1	1.4	3	3.2
A13	3.3	3.5	3.6	0.8	1.7	2.6	3	1	4.1	5.5	3.7	3	1.3	0	1.6	2.4	1.9	3.1	3	3.3	2.6	4.2	4.5
A14	3.8	4.5	4.9	1.8	2.4	3.3	3.9	1.6	4.6	5.6	4.2	3.1	1.9	1.4	0	0.8	1.7	1.8	2	2.8	2.8	3.7	3.9
A15	4.4	5.3	5.7	2.6	3.6	4.1	4.7	2.4	5.4	6.3	5	4.1	2.7	2.2	1	0	2.4	1	1.6	3.5	3.4	4.4	3.2
A16	4.7	5	5.3	2.3	2.6	3.7	4.3	2.1	5	4.2	3	1.7	0.7	1.8	1.7	2.3	0	1.6	1.4	1.7	1.3	2.6	2.9
A17	5.7	6.3	6.6	3.6	4.5	5	5.7	3.4	6.3	5.7	4.5	3.2	2.2	3.2	1.6	1	1.6	0	0.9	2.1	2.8	3.8	2.5
A18	5.6	6.3	6.5	3.5	4.4	4.8	5.6	3.2	6.2	5.3	4.1	2.9	1.8	3	2	1.5	1.4	0.95	0	1	3.3	2.7	1.8
A19	5.9	6.4	6.8	3.8	4.3	5.2	5.8	3.5	6.5	5.2	4	2.9	2.2	3.4	2.6	2.8	2.4	2.1	1	0	1.9	1.4	1.6
A20	5.1	5.7	6	3	3.9	4.4	5.1	2.8	5.7	4.3	3	1.3	1.4	2.6	2.1	2.9	0.7	2.2	1.8	2.1	0	3	3.2
A21	7.4	7.9	8.3	5.2	6.2	6.7	7.3	5	8	4.7	4.6	2.8	3.6	4.6	4.3	4.7	3.9	4.4	4	2.6	2.5	0	2
A22	7.1	7.7	8	5	5.5	6.6	7.1	4.8	7.7	5.7	4.3	3.3	3.4	4.6	4.1	3.3	2.7	3.6	3.9	1.5	2.3	1.7	0

Fig 5. Distance matrix (km)

Label	Depot	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21	A22
Depot	0	5	9	8	9	11	9	10	14	20	14	16	11	11	11	13	13	15	15	15	14	17	17
A1	4	0	8	11	12	13	10	12	16	22	16	19	15	14	15	15	17	18	18	19	18	20	21
A2	11	9	0	10	10	7	7	9	11	18	12	17	13	11	14	16	15	18	18	18	16	20	20
A3	8	9	10	0	4	8	8	4	11	15	9	9	5	4	5	6	7	9	9	10	8	11	12
A4	9	10	11	4	0	6	6	3	9	14	8	12	7	4	8	10	9	12	11	12	10	14	14
A5	13	13	8	8	7	0	5	5	6	14	9	13	9	8	10	12	11	14	13	14	12	17	16
A6	12	11	4	7	6	4	0	6	8	16	10	14	10	7	11	13	12	15	14	15	13	17	18
A7	10	12	11	4	3	6	7	0	7	12	6	10	5	2	7	9	7	11	10	10	8	12	12
A8	17	17	11	13	11	7	9	9	0	16	13	17	14	11	15	17	16	19	19	19	17	21	22
A9	20	22	18	14	13	13	15	11	14	0	5	9	9	13	14	15	10	14	13	13	10	12	15
A10	16	18	13	9	8	8	10	7	10	6	0	5	5	8	8	11	6	10	8	8	6	9	11
A11	15	17	16	9	10	13	14	8	15	9	5	0	4	8	8	10	5	9	8	8	4	6	8
A12	11	13	14	5	7	9	10	4	11	12	10	6	0	4	7	8	3	7	8	8	4	8	9
A13	9	11	12	3	5	8	10	4	10	15	9	9	4	0	6	7	6	9	9	10	8	12	12
A14	11	13	14	5	8	10	11	6	12	16	11	10	6	5	0	3	5	5	6	8	8	10	10
A15	12	15	16	7	9	11	12	7	14	18	12	11	7	8	3	0	7	4	6	9	10	11	11
A16	13	14	15	7	8	10	11	5	12	12	8	6	2	6	5	7	0	6	5	5	4	7	7
A17	14	16	16	9	11	13	13	9	15	16	12	9	6	9	6	4	6	0	3	6	8	9	8
A18	14	16	16	9	11	13	15	9	15	15	12	9	5	9	6	6	5	3	0	3	7	7	6
A19	15	16	16	10	12	14	16	10	17	14	11	7	7	10	8	9	6	6	3	0	5	5	5
A20	13	17	17	8	10	13	14	8	14	12	8	5	5	8	6	7	2	6	5	6	0	8	8
A21	18	21	22	13	15	17	18	12	19	13	12	7	9	13	11	13	7	11	10	8	6	0	6
A22	17	21	21	13	15	16	18	12	18	15	11	8	9	12	11	10	7	7	6	5	6	5	0

Fig 6. Time matrix (minutes)

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Initial Delivery Route

The following are the initial routes used by the Medan City distribution center to carry out inter-area distribution.

Table 5. Initial Conditions of Individual Routes

No	Route	Distance	Time	No	Route	Distance	Time
1	Depot-A1-Depot	2.9	9	12	Depot-A12-Depot	8	22
2	Depot-A2-Depot	5.8	20	13	Depot-A13-Depot	6.6	20
3	Depot-A3-Depot	4.9	16	14	Depot-A14-Depot	7.4	22
4	Depot-A4-Depot	5.6	18	15	Depot-A15-Depot	9.1	25
5	Depot-A5-Depot	8.5	24	16	Depot-A16-Depot	9.2	26
6	Depot-A6-Depot	6	21	17	Depot-A17-Depot	11.1	29
7	Depot-A7-Depot	7	20	18	Depot-A18-Depot	11	29
8	Depot-A8-Depot	12.2	31	19	Depot-A19-Depot	11.6	30
9	Depot-A9-Depot	15.8	40	20	Depot-A20-Depot	10.2	27
10	Depot-A10-Depot	11.5	30	21	Depot-A21-Depot	14	35
11	Depot-A11-Depot	11.4	31	22	Depot-A22-Depot	13.9	34

As illustrated in Table 5, the initial conditions for the total distance to be traveled are 203.7 km, and the total time is 559 minutes.

Intermediete Area Clustering Results

To optimize the division of the work area, a clustering process was executed via the Elbow Method. The objective of this methodology is the determination of the most suitable numerical value for the number of clusters by means of an examination of the WCSS. An analysis of this data set indicated that its optimal partitioning into clusters would be into four clusters, which were subsequently designated clusters 0, 1, 2, and 3.

The ensuing key findings emerged from the subsequent analysis of these clustering outcomes.

1. The first cluster is comprised of five delivery areas: Area 8, 9, 10, 11, and 21. The aggregate demand for these areas is 86.
2. Cluster 1 comprises seven delivery areas (areas 3, 4, 5, 6, 7, 12, and 13) with a cumulative demand of 110.
3. Cluster 2 comprises two delivery areas, designated as Area 1 and Area 2, with a cumulative demand of 100.

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4. Cluster 3 encompasses eight delivery areas (Areas 14, 15, 16, 17, 18, 19, 20, and 22), collectively accounting for total demand 104.



Fig 7. Results of delivery area clustering

Fleet Capacity and Operations

According to direct observations, the mean load capacity of each vehicle is 40 parcels for each trip, and three trips are completed daily. The designated vehicles for this purpose are two-wheelers, typically 110–150 cc scooters or automatic motorcycles. These vehicles are selected for their superior efficiency and agility, which renders them particularly well-suited for daily distribution operations. These motorcycles are equipped with panniers on both the left and right sides, crafted from waterproof canvas or tarpaulin. Each pannier possesses a capacity of approximately 20–25 kilograms, rendering them suitable for the transportation of both parcels and correspondence. The utilization of motorcycles for the purpose of freight transportation is subject to a set of regulations, which are outlined in the Minister of Transportation Regulation and the implementing rules under the Land Transportation Law. These regulations stipulate that the load must not exceed the width of the handlebars, must not extend more than 90 centimeters above the seat, and must be positioned behind the rider. These measures are implemented to ensure safety and stability during the transportation process. Depending on variables such as distance and traffic conditions, a single courier is estimated to be capable of delivering approximately 120 packages per day.

Determining the Number of Couriers

The results of the data analysis conducted on the four established clusters indicated that the ideal quantity of delivery personnel is equivalent to four individuals, with a maximum daily

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capacity of 120 parcels per individual. The maximum package capacity of the vehicle was determined to be 40 units per trip. The hypothesis is that this configuration will enable the company to distribute goods to all areas while maintaining an even workload distribution, with no need for a substantial increase in the number of couriers. This approach offers two primary advantages: a reduction in operational costs, specifically those related to fuel and labor hours, and an enhancement in productivity per courier.

Table 6. Number of Couriers Required

Cluster	Demand/Day	Number Trips/Day	Capacity Cargo/Day/Courier	Total Couriers
0	86	3	120	1
1	110	3	120	1
2	100	3	120	1
3	104	3	120	1

In-house Implementation Costs

This cost model is meticulously designed to provide a comprehensive and precise estimation of the in-house costs. The study's distinguishing feature is its comprehensive nature, encompassing both CAPEX and OPEX for 5-year period. Total of vehicles in this simulation, specifically motorcycles and couriers, is derived through a calculation of the optimal number of couriers. This calculation determines that the optimal number of couriers is four. The subsequent table presents the results of the investigation.

Table 7. In-House Model Costs

Component	5-Year Total Cost	Monthly Average Cost
CAPEX Depreciation	32.349.925	539.165
Salaries Cost	1.082.440.353	18.040.673
Allowances Cost	238.000.000	3.966.667
Insurance Cost	36.000.000	600.000
Fuel Cost	96.000.000	1.600.000
Maintenance Cost	15.000.000	250.000
Tax Cost	5.000.000	83.333
Total Cost	**Rp 1.504.790.278**	**Rp 25.079.838**

As illustrated in Table 7, the monthly cost of employing an in-house operations model amounts to Rp. 25,079,838, which is marginally less than that of the outsourced operations model.

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It is estimated that the implementation of the in-house operations paradigm will engender cost savings of approximately 7.11%. It is important to acknowledge that these estimates do not encompass the potential for achieving further efficiencies through the implementation of route optimization strategies.

CVRP – Clarke and Wright Savings

The subsequent findings emerged from the implementation of the CVRP - Clarke and Wright Saving model.

Table 8. Results of the CVRP - Clarke and Wright Saving Model

Area Cluster	Route	Distance Travel	Travel Time	Demand	Number of Iterations	Number Trips
0	Depot - A8 - A9 - A10 - A11 - A21 – Depot	24.2	64	86	4	3
1	Depot - A6 - A5 - A7 - A13 - A12 - A3 - A4 – Depot	13.4	42	110	6	3
2	Depot - A1 - A2 - Depot	7.3	24	100	1	3
3	Depot - A14 - A15 - A17 - A18 - A22 - A19 - A20 - A16 – Depot	17.1	52	104	7	3
Total		**62**	**182**	**400**		

From Table 8 above, it can be seen that with the application of the developed CVRP CWS model, the total distance and travel time are 62 km and 182 minutes. Specifically,

1. Total distance and travel time required for Cluster Area 0 are 24.2 km and 64 minutes.
2. Total distance and travel time required for Cluster Area 1 are 13.4 km and 42 minutes.
3. Total distance and travel time required for Cluster Area 2 are 7.3 km and 24 minutes.
4. Total distance and travel time required for Cluster Area 3 are 17.1 km and 52 minutes.

A comparison with the initial conditions is shown in the table below.

Table 9. Comparison of Initial Conditions vs. CVRP CWS

Area Cluster	Distance Initial Travel	Time Initial Travel	CWS Distance	CWS Travel Time	Distance Saved	Time Savings
0	64.9	167	24.2	64	40.7	103

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1	46.6	141	13.4	42	33.2	99
2	8.7	29	7.3	24	1.4	5
3	83.5	222	17.1	52	66.4	170
Total	**203.7**	**559**	**62**	**182**	**141.7**	**377**

Table 9 above shows that by applying the developed model, operational efficiency improves because delivery time and distance are shorter compared to the initial conditions, as shown in the information below:

1. Optimal total distance for all areas: 62 KM.
2. Optimal total time for all areas: 182 minutes.
3. Total baseline distance (each customer served separately) for all areas: 203.7 KM.
4. Total baseline time (each customer served separately) for all areas: 559 minutes.
5. This optimization resulted in significant savings.
    a) 141.7 km in distance.
    b) 377 minutes in time.

CVRP – Genetic Algorithm

The subsequent findings were derived from the development of the CVRP - Genetic Algorithm model:

Table 10. Results of the CVRP - Genetic Algorithm model

Area Cluster	Route	Distance Travel	Travel Time	Demand	Number of Generations	Number Trips
0	Depot - A8 - A9 - A10 - A11 - A21 - Depot	24.2	64	86	0	3
1	Depot - A6 - A5 - A4 - A7 - A13 - A12 - A3 – Depot	13.2	42	110	49	3
2	Depot - A2 - A1 - Depot	6.9	22	100	0	3
3	Depot - A14 - A15 - A17 - A18 - A19 - A22 - A20 - A16 – Depot	16.8	50	104	4	3
Total		**61.1**	**178**	**400**		

From Table 10 above, it can be seen that with the application of the developed CVRP GA

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model, the total distance and travel time are 61.1 km and 178 minutes. Specifically,

1. Total distance and travel time required for Cluster Area 0 are 24.2 km and 64 minutes.
2. Total distance and travel time required for Cluster Area 1 are 13.2 km and 42 minutes.
3. Total distance and travel time required for Cluster Area 2 are 6.9 km and 22 minutes.
4. Total distance and travel time required for Cluster Area 3 are 16.8 km and 50 minutes.

A comparison with the initial conditions is shown in the table below.

Table 11. Comparison of Initial Conditions vs. CVRP GA

Cluster Area	Distance Initial Travel Time	Time Initial Travel Time	Distance Travel Time GA	Time Travel Time GA	Distance Saved	Time Savings
0	64.9	167	24.2	64	40.7	103
1	46.6	141	13.2	42	33.4	99
2	8.7	29	6.9	22	1.8	7
3	83.5	222	16.8	50	66.7	172
Total	**203.7**	**559**	**61.1**	**178**	**142.6**	**381**

From Table 11 above, it can be seen that by applying the developed model, operational efficiency increases because delivery time and distance are shorter compared to the initial conditions, as shown in the information below:

1. Total optimal distance for all areas: 61.1 KM7.
2. Optimal total time for all areas: 178 minutes.
3. Base total distance (each customer served separately) for all areas: 203.7 KM.
4. Total baseline time (each customer served separately) for all areas: 559 minutes.
5. This optimization results in significant savings.
    a) 142.36 KM in distance.
    b) 381 minutes in time.

Comparison of the Efficiency and Risk of the Two Models

In light of the model processing and development that has been executed, the ensuing findings emerge from the successful determination of spatial and temporal distance calculations.

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Table 12. Results of Distance and Travel Time Calculations

Area	Initial Conditions		CVRP CWS		CVRP GA	
	Distance	Time	Distance	Time	Distance	Time
Cluster 0	64.9	167	24.2	64	24.2	64
Cluster 1	46.6	141	13.4	42	13.2	42
Cluster 2	8.7	29	7.3	24	6.9	22
Cluster 3	83.5	222	17.1	52	16.8	50
Total	**203.7**	**559**	**62**	**182**	**61.1**	**178**

The following table presents a comparison of the outsourcing model utilized for LMD with that of the in-house approach. The basis for this comparison is the results of the distance and travel time calculations in Table 12, as well as the financial estimates for the outsourcing paradigm in Table 4, and for the in-house model in Table 7. The CVRP with the CWS method and the CVRP with the Genetic Algorithm method were used to make these comparisons. The results of these comparisons are shown below.

Table 13. Comparison of Efficiency and Risk Between Models

Aspect	Outsourcing Partner	In-House + CVRP CWS	In-House + CVRP Genetic Algorithm
Cost per Package	Rp 2,250	Rp 2,090	Rp 2,090
Monthly Fee	Rp 27,000,000	Rp 25,079,838	Rp 25,079,838
CAPEX	None	Yes	Yes
Operational Risk/Hazard	Low	Higher	Higher
Quality Control/Assurance	Limited	Higher	Higher
Scalability	High	Medium	Medium
Route Efficiency	-	Optimal	Optimal
Future Efficiency Potential	Limited	High	High
Number of Couriers (People)	7	4	4
Distance (KM)	203.7	62	61.1
Time (minutes)	559	182	178
Mileage Efficiency (KM)	-	141.7	142.6
Time Efficiency (Minutes)	-	377	381

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As illustrated in Table 13, the in-house model employing the CVRP method demonstrates superiority in multiple domains, including cost, quality control, route efficiency, long-term efficiency potential, mileage efficiency, and travel time efficiency. Nevertheless, companies are obliged to implement comprehensive risk management protocols, particularly regarding protocols for fleet management, protocols for courier instruction, and protocols for the evaluation of performance, to guarantee the operational dependability of the aforementioned systems.

CONCLUSION

A comprehensive evaluation was conducted to ascertain the efficacy of various methodologies in enhancing delivery distribution efficiency. This evaluation was informed by a meticulous analysis of actual delivery distribution data, followed by a systematic operational analysis and route optimization simulations. The evaluation focused on operational costs, total distance traveled, delivery time, and the creation of optimal delivery routes for LMD activities at PT Pos Indonesia Medan Kota. The research findings and discussions lead to the following conclusions:

1. The determination of a more optimal operating model was carried out by comparing the existing operating model (outsourcing) with the in-house operating model. The in-house operational model, with an average monthly cost of Rp. 25,079,838, proved slightly more efficient than the outsourcing model, which has an average monthly cost of Rp. 27,000,000, resulting in a total efficiency gain of 7.11% (Rp. 1,920,162) per month.
2. The determination of the optimal distribution route was conducted by comparing the existing distribution route with the optimization results using the CVRP CWS method and the CVRP Genetic Algorithm. The CVRP Genetic Algorithm model provided more optimal results compared to the CVRP Clarke and Wright Savings model.
3. The CVRP Clarke and Wright Savings method resulted in a travel distance of 62 km with a travel time of 182 minutes, while the CVRP Genetic Algorithm method resulted in a travel distance of 61.1 km with a travel time of 178 minutes. Meanwhile, the existing distribution route without optimization requires a travel distance of 203.7 km with a travel time of 559 minutes. Thus, the CVRP Genetic Algorithm provides the highest operational efficiency compared to other methods.
4. Implementation of the CVRP Genetic Algorithm model results in a travel distance savings of 142.6 km or approximately 70% compared to the existing distribution route, and is 0.9 km more efficient than the CVRP CWS model.

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5. Furthermore, implementation of this CVRP Genetic Algorithm model has been shown to result in a travel time savings of 381 minutes, or approximately 68.16%, when compared to the existing distribution route. This result is 4 minutes more efficient than the CVRP Clarke and Wright Savings model. Based on these results, it can be seen that the use of the appropriate optimization method has great potential to support efficiency in distance and travel time for distribution, particularly for last-mile delivery activities at the PT Pos Indonesia Distribution Center in Medan Kota.

Recommendation

1. Although the implementation of an in-house operational model using the CVRP Genetic Algorithm method requires a relatively larger initial investment and carries a higher level of operational risk compared to the outsourcing model, this model is considered capable of providing strategic advantages in the long term. These advantages include improved operational control, higher quality of distribution services, greater flexibility in fleet management, and sustainable operational cost efficiency. Therefore, the results of this study can serve as one of the considerations in determining operational strategies for last-mile delivery activities at PT Pos Indonesia.
2. This study also recommends that PT Pos Indonesia consider the phased implementation of an in-house operational model supported by the CVRP Genetic Algorithm method, particularly in distribution areas with high delivery volumes. This phased implementation is expected to facilitate the operational adaptation process while minimizing implementation risks. In addition, the company is advised to develop an integrated and reliable system for monitoring distribution performance, fleet tracking, and vehicle maintenance to support optimal operational sustainability.
3. Future research is recommended to develop a more adaptive distribution optimization model through the application of dynamic routing based on real-time traffic data. Furthermore, integrating optimization methods with predictive analytics could also be considered to improve the ability to forecast future demand and distribution conditions. With this approach, the operational efficiency of last-mile delivery (LMD) is expected to continue improving in a more accurate, responsive, and sustainable manner.

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