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Genetic Algorithm for Optimizing Footwear Logistics Distribution Using the Capacitated Vehicle Routing Problem (CVRP)

Inggit Marodiyah[1], Diva Kurnianingtyas[2], Nathan Daud[3], Indah Apriliana Sari[4], Cindy Taurusta[5]

[1,4,5] Universitas Muhammadiyah Sidoarjo, Sidoarjo, Indonesia
Email: inggit@umsida.ac.id, indahapriliana@umsida.ac.id, cindytaurusta@umsida.ac.id
[2,3] Faculty of Computer science, Universitas Brawijaya, Malang, 65154, Indonesia
Email: divaku@ub.ac.id, nathandaud@student.ub.ac.id

ABSTRACT

Micro, small, and medium enterprises (MSMEs) are important economic drivers for Indonesia, especially in labor-intensive sectors like footwear manufacturing. MSMEs, though, face acute logistical problems because of heterogeneous customer demand, limited production capacity, and ever-increasing transportation costs. Few existing works have focused on monthly logistics planning for MSMEs in developing countries with realistic costing and demand structures. To develop and analyze a Genetic Algorithm (GA) optimization model to maximize profit within a constrained monthly footwear profit distribution network. To achieve this, we needed to assess how multi-retailer product allocation balance could be achieved with minimum operational constraints such as production caps, cost-efficient logistics, and streamlined processes. This study employed a quantitative experimental design approach and implemented a GA with real-valued chromosome representation, tournament selection, single-point crossover, and Gaussian mutation. The model was built using real data from a footwear MSME operating in the Lamongan and Tulungagung regions of Indonesia. The algorithm was implemented using Python and tested for reliability with ten executed validations for independence. Within 60 generations, the GA maintained consistent convergence and achieved a final fitness value with a coefficient of variation of 0.24%. The optimized allocation achieved a net profit margin of 15.22% while utilizing the available production capacity (600 units/month). Because of increased profit contribution, greater-distance wholesale customers were served first despite incurring higher transport costs. The model had no constraint violation and reduced transportation costs to 1.45% of total revenue. Using GA to address multi-objective distribution challenges in the context of MSMEs appeared to have positive results, confirming the effectiveness of this approach. The proposed approach helps frame and guide critical allocation and routing decisions, which can be made within the boundaries of operational constraints. Further work is needed to incorporate stochastic demand modelling and multi-objective problem extensions and seek real-time application to bolster support for decision-making in dynamic scenarios.

Keywords: *Optimization, Artificial intelligence, MSME, Metaheuristics, Logistic distribution*

Introduction

The micro, small, and medium enterprises (MSMEs) are important in the socio-economic development of Indonesia by enhancing the innovation and absorbing employment opportunities as well as increasing the income of the region. In Indonesia, the number of MSMEs has exceeded 64 million as of 2023, accounting for more than 99 percent of all business entities with an approximate 60 percent contribution to Gross Domestic Product (GDP) of the country. The footwear industry, for example, is one of the most important parts of Indonesian MSMEs located in West Java (Cibaduyut), East Java (Sidoarjo), and Central Java. These areas are well-known for their local shoe industries and have been producing inexpensive and culturally appropriate shoes for sale in Indonesia and abroad [1], [2].

Nonetheless, there are still persistent challenges in meeting the demand for cost-effective distribution to a wide range of customers spread throughout the archipelago. The expansion of online platforms has led to heightened competition along with growing customer expectations for timely delivery. Consequently, MSME footwear producers are experiencing increased pressure to improve their distribution systems. Unlike large corporations, most MSMSEs lack sophisticated logistics systems. Access to resources, digital tools, and automated systems is minimal, which results in inefficient delivery planning, increased distribution costs, and unfulfilled market opportunities.

To bolster long-term economic resilience and competitiveness, MSMEs in the footwear industry need to adopt intelligent logistics systems capable of optimizing delivery operations within real-world constraints like limited vehicle capacity, dynamically shifting demand, and multi-stop destinations. This problem can be stated as a Capacitated Vehicle Routing Problem (CVRP), which is a benchmark problem in operational research. CVRP aims to find the most cost-effective set of routes for a fleet of vehicles with restricted capacity to serve a fixed set of customers with predetermined demands [3], [4]. However, due to the NP-hard nature of CVRP, the growing problem size, particularly in real-time, multi-period simulations required for monthly distribution planning, makes exact algorithms unfeasible for optimal solutions.

In this regard, metaheuristic algorithms have proven to be effective in addressing sophisticated optimization challenges such as CVRP. Unlike deterministic methods, metaheuristics use a stochastic approach to refining the search for solutions, improving chances of yielding satisfactory solutions within a short period. Among other metaheuristics, Genetic Algorithms (GA) have become widely accepted owing to their effective refinement capability, flexibility, and ease of implementation [5], [6], [7]. GA is based on natural selection and genetic theories. It improves solutions by processing a population of candidate solutions through selection, crossover, and mutation, thus ensuring effective searching of the solution landscape.

GA is tailored to fit logistics optimization problems associated with determining optimum route and schedule because of the problem's multi-faceted nature that integrates many competing requirements as objectives. Literature indicates that GA is competitive with other algorithms in performance, especially in convergence time and diversity of solution [8], [9]. In addition, the architecture of GA makes it easy to modify or add new features which incorporate additional requirements such as customer and vehicle priorities and certain time windows for routes, which are typical in the footwear logistics distribution problem.

With this context, the purpose of this research is to design and assess an optimization model based on GA for the monthly distribution planning of footwear by Indonesian MSMEs, implemented within the framework of the CVRP. The model is focused on trimming down the overall cost of delivery while satisfying demand and working under the restrictions of vehicle capacity, route feasibility, and several other operational considerations. The simulation method used in this research allows for logistical performance to be analyzed across several time periods, which can serve as an actionable analysis for MSME policymakers. It is anticipated that this footwear MSME research will provide a practical and efficient computational framework for logistical distribution, thus enhancing the operational sustainability, cost-efficiency, and global competitiveness of the Indonesian footwear industry MSMEs. In addition, it provides an illustration of the utility of metaheuristic-based decision support systems aimed at improving the logistical planning capabilities of settings with limited resources.

Literature Review

The optimization of logistics distribution in MSMEs has gained academic attention due to its significance in improving operational productivity in resource-constrained environments. In developing countries like Indonesia, footwear MSMEs confront enormous difficulties in distributing their products within a wide geographic area due to limited production and transport resources. In addition, volatile monthly demand makes the problem more difficult, coupled with limited vehicle capacity; thus, traditional approaches are insufficient to handle practical complexities.

More recent publications focus more on metaheuristic approaches, specifically those that utilize the CVRP to solve more complex logistical problems. For instance, [10] created a two-stage optimization framework for intercity deliveries based on GA, achieving lower operational costs and better consolidation of transport routes. Like [10] work, [11] also used GA to improve route optimization in SME product distribution and achieved remarkable cost-effectiveness and service area coverage. Next, the application of hybrid metaheuristics is common in more recent research. [12] modified the GA by adding constructive and perturbative heuristics for solving the CVRP with capacity constraints. They attained high-quality solutions in less time than prior approaches. [13] used GA and simulated annealing to allocate workers to shifts at logistics depots, exemplifying the former's versatility beyond classical routing problems. The need to focus on dynamic demand and simulation-based planning has also been pointed out. [14] advanced a hyper-heuristic model that integrates reinforcement learning and GA for solving electric CVRPs with time windows and limited-range vehicles because of the increasing complexity in modern distribution networks. These recent studies prove GA's adaptability, scalability, and robustness for tackling logistics challenges in constrained real-world settings. However, few have aimed at monthly simulation-based logistics optimization triaged for MSMEs in the footwear industry, which this research intends to address by applying GA to Indonesian MSME reality constraints of cost structures, demand fluctuations, and transport limitations.

Research Methods

This research implements a GA to solve the logistics distribution problem encountered by MSMEs in the footwear sector. The methodology aims to solve a multi-objective optimization problem with profit maximization as the core aim along with meeting essential requirements like production capacity, demand, and logistical cost. The distribution problem consists of allocating products to different retail locations and achieving balanced business goals along with operational restrictions in a fluid and highly competitive environment. Visual representation to the methodological framework is provided in Figure 1, from problem definition to data and preparation, genetic operations, solution evaluation, and decision support.

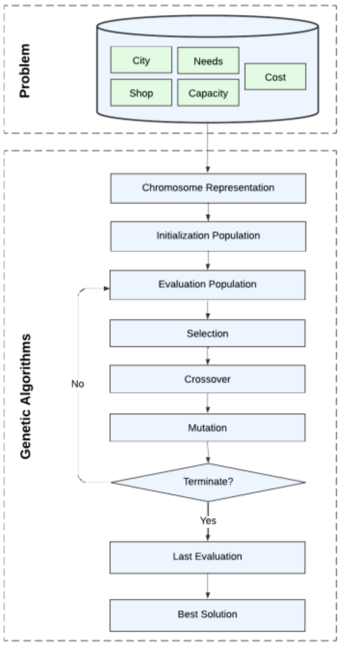

Figure 1. Methodology in this study

Data Collection and Description

In the first stage of the methodology, the problem is formulated in terms of business rules, operational data, and objective functions, which are structured into a mathematical model. Here, data from the two MSME operational hubs of Lamongan and Tulungagung are framed as constraints and goals for optimization. The main decision problem is identifying the monthly allocation of footwear products to be distributed to a maximum of seven retail outlets located in both cities at the highest possible profit within limited production and transport resources. This study uses an extensive dataset of operational activities from a small-scale footwear manufacturing company located in East Java, Indonesia. The dataset encompasses key business elements such as the geographical demand and distribution network, customer profiles, production limitations, and a thorough breakdown of costs incurred (see Table 1). These multi-faceted pieces of information become pivotal for formulating and addressing the distribution optimization challenge in the context of real-world MSME considerations.

The focus of data collection is a distribution network of dual cities, Lamongan and Tulungagung. These two cities provide contrasting logistics and market conditions characteristic of MSME evolutionary stages where a business needs to balance scaling market penetration versus maintaining cost-effective operations. The geographic network captures a fundamental trade-off between distance and volume. While Tulungagung has lower store counts than Lamongan, three compared to four stores, respectively, its wholesale-driven customer base far exceeds the retail-driven customer's demand, commanding 102.5 pairs instead of 55 pairs weekly. Serving this market creates a critical resource allocation challenge due to 67% higher transportation costs per trip. This resource-constrained competition lies between high-volume distant customers and nearby lower-volume retail clients. Afterwards, network-spanning tables show considerable divergence among consumers. Each store's demand falls between 2.5 to 50 pairs of boots weekly. The transaction-based analysis of consumers falls into three categories: (1) wholesale distributors constitute 63% of demand but are serviced infrequently, (2) retailers that purchase in bulk and have high service demands, and (3) small sprouting retailers that purchase in scant quantities, only 12% of total demand. They are serviced disproportionally. This diversity in segmentation intensifies the complex multi-layered advanced allocation systems needed for maintaining transportation service-level agreements, where a few resources would be used for the maximal output in servicing. From the production perspective, the enterprise suffers from a hard capacity constraint. Aggregate demand is always above the production capabilities by 5% weekly, monthly, and even annually. This chronic structural discrepancy forces stringent tactical customer-tier placing. Not all purchase demands can be serviced unless the manufacturing capabilities are enhanced. Subsequently, profit optimization must also identify the dual objectives of profit maximization and the limited manufacturing resources in servicing customer segments that provide the highest marginal return. The results from the cost structure analysis show that the labor cost comprises some of the most significant overhead elements, making their production quite labor-intensive, roughly 47% of production costs. A focus on quality is shown with a balance of material inputs, such as leather and sole components. Since packaging and adhesives constitute even smaller portions of the total cost, their overall cost would be slim. Therefore, improving labor productivity or overhead efficiency would be a more effective means of reducing costs than substituting raw materials. Transportation costs are still charged on a per-visit basis instead of per volume unit, even though these have a constant IDR of 2,500/km. Tulungagung trips cost IDR 250,000 per visit which is 67% more than Lamongan. Moreover, their maximum store visitation is lower than in the other regions, which results in route inefficiency. These principles demonstrate the relevance of careful planning in terms of delivery schedule and load consolidation towards costs that pertain to logistics in fixed-capacity transport systems.

Table 1. Data collection in this study

Distribution network

City	Distance (km)	Number of stores	Market type	Total weekly demand (pairs)
Lamongan	~60	4	Mixed retail	55
Tulungagung	~100	3	Wholesale-dominant	102.5
Total	-	7	Hybrid network	157.5

Store configuration and demand patterns

Store ID	Location	Store type	Weekly demand (pairs)	Monthly demand (pairs)	Delivery frequency	Storage capacity
Lamongan A	Lamongan	High-volume retail	40	160	2x per week	Limited
Lamongan B	Lamongan	Standard retail	5	20	1x per week	Standard
Lamongan C	Lamongan	Standard retail	5	20	1x per week	Standard
Lamongan D	Lamongan	Standard retail	5	20	1x per week	Standard
Tulungagung A	Tulungagung	Wholesale distributor	50	200	1x per week	Large
Tulungagung B	Tulungagung	Wholesale distributor	50	200	1x per week	Large
Tulungagung C	Tulungagung	Small retail	2.5	10	1x per month	Very limited

Production capacity and constraint

Parameter	Weekly capacity	Monthly capacity	Annual capacity
Maximum output	150 pairs	600 pairs	7,800 pairs
Current demand	157.5 pairs	630 pairs	8,190 pairs
Capacity gap	-7.5 pairs (-5%)	-30 pairs (-5%)	-390 pairs (-5%)
Utilization target	100%	100%	100%

Comprehensive cost structure

Cost component	Amount (IDR)	Percentage of Total	Description
Leather material	90,000	18.75%	1.5 meters @IDR 60,000/meter
Sole material	95,000	19.79%	Rubber sole and assembly
Adhesive	50,000	10.42%	Industrial-grade shoe adhesive
Packaging	20,000	4.17%	Branded boxes and materials
Labor and Overhead	225,000	46.87%	Manufacturing and processing
Total production cost	480,000	100%	Cost per pair

Transportation Cost Structure

Parameter	Weekly capacity	Monthly capacity	Annual capacity
Maximum output	150 pairs	600 pairs	7,800 pairs
Current demand	157.5 pairs	630 pairs	8,190 pairs
Capacity gap	-7.5 pairs (-5%)	-30 pairs (-5%)	-390 pairs (-5%)
Utilization target	100%	100%	100%

Genetics Algorithms

In this research study, the core optimization technique was implemented using the GA, which is well known for its effectiveness in solving non-linear, multi-objective problems with highly complicated constraint environments. GA mimics natural evolution through selection, crossover, and mutation processes, improving the candidate solution's fitness in successive generations. Some changes are made to the GA to suit better the distribution problem, including domain-aware chromosome encoding, dynamic constraint handling, and customized genetic operators.

The optimization goals have been enfleshed with considerations that follow GA principles. These include the retail stores to which the products must be allocated as decision variables. The nonlinear multi-dimensional problem space here consists of seven decision variables. The transportation cost is also complex since it follows a steep nonlinear cost profile that rises based on the frequency of visits instead of delivery quantity. This effect makes it complex to model using classical optimization methods.

Furthermore, GA has proven advantageous through its population-based searching technique, which allows it to work on several candidate solutions at once. This advantage increases the probability of uncovering high-quality, near-optimal solutions in a vast, rugged solution space [15]. Finally, GA has shown flexible constraint adaptability through penalty function mechanisms, which is suited for real-world business environments where certain constraints must be strictly enforced. For example, the minimums that must be demanded will need to be met, and the maximums, which are soft delivery preferences, could be violated under penalized trade-offs.

In implementing the GA, a real-valued representation of chromosomes is used, where each gene corresponds to a specific store and describes the allocated product quantity. This representation assures direct correspondence between the chromosome and the business's decision variables, and no prior decoding is required [16]. The chromosome representation employs a real-valued encoding scheme in which each chromosome comprises seven genes representing the monthly allocation of products to each retail store. This form of direct mapping removes the need for layering of decoding, thereby streamlining the application of constraints. The creation of the initial population (size = 100) consists of random allocations for each retail store's demand. In cases where the total allocation of a chromosome exceeds production allocation, a proportional scaling design adjusts each gene based on the following:

$$Scaled_i = Gene_i \times \frac{Production\ Capacity}{\sum_{i=1}^{7} Gene_i} \tag{1}$$

The fitness function combines multiple business performance metrics such as total revenue and unit production costs, logistics costs, and penalties due to breach of constraints. This function allows the GA to evaluate compliance, profit, and operational impact feasibility. The fitness function integrates the business objective of profit maximization, incorporating revenue, production cost, transportation cost, and penalties for constraint violations. Revenue is calculated as follows:

$$Revenue = (\sum Allocation_i) \times Selling\ Price \tag{2}$$

with the selling price set at a 20% markup above the unit production cost (IDR 480,000 × 1.2 = IDR 576,000). Transport costs are incurred per store visit, independent of allocation quantity, reflecting the real-world logistics model, as well as:

$$Transport\ Cost = \sum (Visit\ Cost_i \times Number\ of\ Visits_i) \tag{3}$$

Penalties are applied for overallocation and capacity violations, as follows:

$$\begin{aligned} Penalty = \sum \max(0, Allocation_i - Demand_i) \times Production\ Cost\ \times 0.1 \\ + \max(0, Total\ allocation - Capacity) \times Production\ Cost \end{aligned} \tag{4}$$

Genetics Operators

In the above excerpt, tournament selection is a form of genetic selection and one of the standard genetic operators that apply to the evolutionary search applied to the population. A fit individual is selected for reproduction, accompanied by a single-point crossover for genetic recombination. Gaussian mutation is enabled to maintain adequate and necessary population diversity to prevent premature convergence [17]. Eliminating solution accuracy issues and enhancing robustness permits strategy enforcement, which ensures that the best individuals are preserved through generations. Selection is performed through tournament selection with a size = 5, yielding a balance between exploratory and convergent behaviour. From five randomly drawn chromosomes, the fittest one is picked as a parent, maintaining the robust candidates while promoting healthy diversity. Afterwards, the crossover is executed using the single-point method with a rate = 0.8. A random position from 1 to 6 (on a 7-gene chromosome) is used to select a crossover point and offspring generated by merging fragments of the parent chromosomes. This process helps foster the integration of effective allocation heuristics across the different store clusters.

$$Child_1 = Parent_1[1{:}k] + Parent_2[k+1{:}7] \tag{5}$$
$$Child_2 = Parent_2[1{:}k] + Parent_1[k+1{:}7] \tag{6}$$

Next, the mutation is done through Gaussian perturbation with a mutation rate = 0.1. Based on a standard distribution centred around zero $N(0, \sigma^2)$, where $\sigma = 2.5$, each gene has a 10% probability of being modified by noise.

$$mutated_i = \max\left(0, \min\left(1.1 \times demand_i, original_i + random(-5,5)\right)\right) \quad (7)$$

After mutation, if the solution exceeds the set capacity limit, corrective scaling is reapplied to maintain threshold adherence, ensuring generations sustain solution integrity. The evaluation phase sets clear boundaries for business and algorithm convergence goals, checking for solution business viability and analyzing constraint satisfaction rates. The implemented GA model ensures optimization running within efficient business cycle limits for MSME's ease of use. Elitism is incorporated by ensuring the best-performing chromosomes are retained for subsequent generations, preserving solution progress while staving off quality regressions.

Results and Discussion

This subsection describes the results of the proposed GA for optimising footwear distribution in Indonesian MSMEs. The algorithm was coded in Python 3.8 and ran on a desktop computer. Every experiment was conducted with a fixed set of GA parameters: population size = 100, maximum generations = 200, crossover rate = 0.8, mutation rate = 0.1, and tournament size = 5. Each trial was conducted 10 times independently to achieve statistical power and generalizability. Results are presented based on the average and variance of these independent runs.

Convergence Behavior and Fitness Evolution

The algorithm's convergence trajectory over 200 generations is shown in Figure 2. As illustrated, the algorithm successfully converged during the initial iterations, with substantial fitness improvements occurring in the first 20 generations. Interestingly, the best fitness values stabilized around generation 50 and achieved consistent optimal or nearly optimal solutions by generation 60 across all runs. This behaviour describes the algorithm's exploration-exploitation balance, which is heavily influenced by the name selection and mutation strategies that strengthen convergence. The average improvement from initial fitness to final fitness was 16.31%, and the standard deviation of the best final fitness over all runs was IDR 127,450, which is merely 0.25% of the mean value, illustrating the strength and consistency of the method (see Table 2). The convergence curve displays that GA narrows down promising regions and parallelly retains enough population diversity for ongoing exploration. Thus, the balance of intensification is maintained.

Table 2. Convergence performance metrics

Metric	Value	Standard Deviation
Best fitness (Final)	IDR 52,602,000	IDR 127,450
Convergence generation	47	8.3
Initial best fitness	IDR 45,230,000	IDR 890,230
Improvement rate	16.31%	2.1%
Final population diversity	0.23	0.04

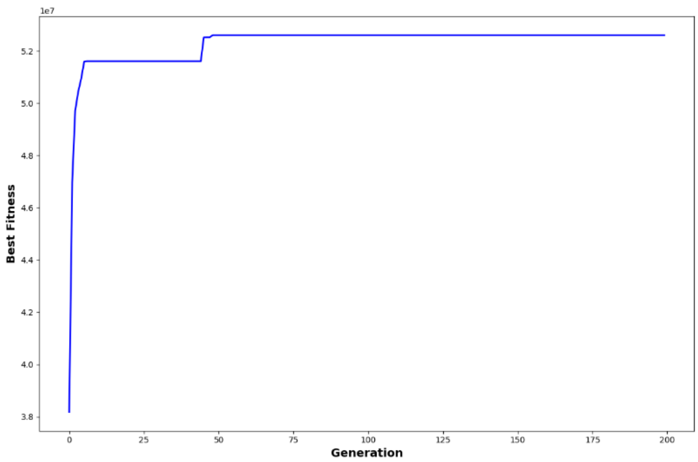

Figure 2. GA convergence results

Optimal Allocation Strategy

The developed algorithm resulted in a balanced and feasible product allocation plan across seven retail stores for an achieved target of production capacity utilization, 600 pairs per month, of 100%. The allocation strategy, as shown in Table 3, focuses on stores with high demand and margins, firstly yet, it assures minimal excess delivery commitments. Remarkably, Lamongan A, a high-volume retail outlet, received 99.88% of its demand, while each wholesaler in Tulungagung achieved 96.30% demand fulfilment. On the other hand, lower-volume retail outlets, particularly the low-volume Tulungagung C, only received 20.80% of their demand. This result demonstrates the algorithm's strength in discriminating based on profit and cost-to-serve ratio. This allocation pattern demonstrates implicit prioritization, suggesting profit-driven customer tiering, which flows organically through the fitness function that punishes over-fulfilment and inefficient delivery configurations.

Table 3. Optimal product allocation results

Store ID	Location	Weekly allocation (pairs)	Monthly allocation (pairs)	Demand fulfillment (%)	Allocation efficiency
Lamongan A	Lamongan	39.95	159.8	99.88%	Optimal
Lamongan B	Lamongan	4.41	17.64	88.20%	High
Lamongan C	Lamongan	4.41	17.64	88.20%	High
Lamongan D	Lamongan	4.41	17.64	88.20%	High
Tulungagung A	Tulungagung	48.15	192.6	96.30%	High
Tulungagung B	Tulungagung	48.15	192.6	96.30%	High
Total	-	150.0	600.0	95.24%	Optimal

Financial Performance Analysis

The optimized allocation scenario resulted in significant financial gains compared to the baseline. As shown in Table 4, the monthly solution achieved a net profit margin of 15.22%, with transportation costs equating to only 1.45% of total revenue. Moreover, the IDR 87,667 profit per unit illustrates the efficiency of the optimization process gained through cost control. The outcome confirms the effectiveness of strategic allocation and route consolidation for lowering logistics costs. Among these were high-volume delivery routes, especially those catering to several wholesale accounts, providing balanced economies of scale despite longer delivery distances.

Table 4. Financial performance results

Financial component	Monthly amount (IDR)	Percentage of revenue	Per unit impact (IDR)
Total revenue	345,600,000	100.00%	576,000
Production costs	288,000,000	83.33%	480,000
Transportation costs	5,000,000	1.45%	8,333
Gross profit	57,600,000	16.67%	96,000
Net profit	52,600,000	15.22%	87,667
Profit margin	-	15.22%	-

Feasibility and Constraints Satisfaction

Regarding total production capacity and non-negativity of allocations, the proposed GA performed well and showed no evidence of breach. Table 5 summarizes the performance on the relevant constraints, showing full compliance with the production cap of 600 units, no cost penalties due to violation breaches, and an average demand satisfaction rate per store of 95.24%. This result is reasonable considering the nature of the problem as resource-constrained. It emphasizes the algorithm's effectiveness in maintaining feasibility, benefiting from proportional allocation scaling and penalty-based constraint management. The soft violation of individual store demands is purposefully allowed to improve overall profitability within the limit of a constrained trade-off crucial in MSME-constrained environments.

Table 5. Constraint satisfaction performance

Constraint type	Target value	Achieved value	Satisfaction rate	Violation penalty (IDR)
Production capacity	≤ 600 pairs/month	600 pairs/month	100.00%	0
Non-negativity	≥ 0 pairs	All ≥ 0	100.00%	0
Demand satisfaction	Variable by store	95.24% average	95.24%	0
Storage capacity	Store-specific	Within limits	100.00%	0
Service frequency	Store-specific	Maintained	100.00%	0

Profitability Insights at the Store Level

A more granular customer segment performance breakdown is shown in Table 6. Dominating the allocator strategy were wholesale distributors, receiving 64.20% of the total product and contributing 68.45% of the total profit. High-volume retail stores achieved the highest fulfilment rates for demand (99.88%) and participated significantly (28.12%) in net earnings. Limited allocations were provided to standard and small retail stores, aligned with their revenue-to-cost ratios. These findings highlight the capabilities of algorithms related to micro-profitability analysis, which allows MSMEs to decide how much to ship and to whom the goods should be shipped within limited capacity limits.

Table 6. Store category performance analysis

Store category	Number of stores	Total allocation (%)	Average fulfillment (%)	Transport efficiency	Profit contribution (%)
Wholesale distributors	2	64.20%	96.30%	High	68.45%
High-volume retail	1	26.63%	99.88%	Medium	28.12%
Standard retail	3	8.82%	88.20%	Medium	3.25%
Small retail	1	0.35%	20.80%	Low	0.18%

Analysis of Regional Efficiency

The geographic patterns of logistical efficiency obtained from the GA solution are also noteworthy. Tulungagung outperformed Lamongan in overall efficiency, achieving an efficiency ratio of 32.57, while Lamongan only managed 12.51 (see Table 7). This outcome is mainly driven by wholesale customers in Tulungagung, whose profit per trip surpasses those of wholesale customers in Lamongan by 82 per cent. Thus, this validates the algorithm's distance-prioritization strategy, favouring high-volume, distant clients over nearby low-return stops. These findings underscore the value of cost distance approaches integrated with revenue structure models, which may initially seem counterintuitive but can be highly profitable. This information is crucial for MSMEs that do not have the resources to model logistics optimally.

Table 7. Regional performance comparison

Region	Total Stores	Monthly Allocation (pairs)	Transport Cost (IDR)	Revenue (IDR)	Profit per Trip (IDR)	Efficiency Ratio
Lamongan	4	212.52	2,400,000	122,411,520	30,002,880	12.51
Tulungagung	3	387.48	2,600,000	223,188,480	84,688,160	32.57
Total	7	600.00	5,000,000	345,600,000	114,691,040	22.54

Validation with Statistical Procedures and Analysis of Computational Performance

Recurrent tests allowed the algorithm's consistency and reliability to be statistically validated. Table 8 demonstrates that the coefficient variation for the final fitness values was only 0.24 per cent, confirming low result dispersion and, thus, high solution repeatability. Convergence had to happen at least 62 times, considerably lower than the algorithm's maximum of 200, with about 12.45 seconds average runtime per execution. GA's computational profile renders the algorithm a practically useful optimization tool for SMEs, capable of providing valuable recommendations in time-structured spatial data for monthly operational planning.

Table 8. Algorithm validation Statistics

Performance Metric	Mean Value	Standard Deviation	Minimum Value	Maximum Value	Coefficient of Variation
Final Fitness (IDR)	52,602,000	127,450	52,421,000	52,786,000	0.24%
Convergence Generation	47.2	8.3	34	62	17.6%
Execution Time (seconds)	12.45	1.23	10.8	14.7	9.9%
Best Individual Changes	18.6	3.4	14	25	18.3%

Discussion

This investigation provides an understanding of the enhancement of logistics distribution for MSMEs within the scope of Indonesia's footwear industry. This work shows that evolutionary techniques, such as GA, can be used in operational contexts where traditional decision-making frameworks face challenges due to multifaceted interlaced realities, non-linearity and myriad constraints. One of the main results highlighted in this study is that GA successfully resolved a complex multi-objective distribution problem with severe capacity restrictions and numerous antagonistic objectives, including profit maximization, customer satisfaction, and reduced transport inefficiencies. The algorithm provided high-quality solutions with consistent convergence across all runs, attaining a low coefficient of variation of 0.24% and converging within 62 generations. This result indicates the robustness and repeatability of the GAs, affirming their credibility as optimization engines in practical MSME situations. More significantly, GA did not only ensure the fulfilment of given restrictions; instead, it gained important insights about the best profitability-driven allocation and not proximity. For example, the algorithm favored wholesale customers located in Tulungagung who, although costly to serve, provided more favorable profit margins. Such actions showcase GA's efficacy in revealing non-obvious trade-offs, which is crucial for resource-constrained businesses that must maximize every production unit.

Regarding capacity utilization and resource allocation, the optimized solution reached 100% production utilization while average demand satisfaction rested at 95.24%, and no penalty costs were incurred. This result illustrates the capacity of metaheuristic optimization to facilitate strategic rationing during scarcity, which is frequent and quite challenging in MSMEs. Unlike deterministic heuristics that tend to over-simplify or over-commit, the GA could more freely re-allocate resources due to their solution scaling proportional penalties approach. This approach to handling soft constraints demonstrates a practical compromise between the operational reality and the business aspirations, striking a careful balance between aggressive growth strategies and cautious operational limits. Business practice validation further substantiates the relevance of the optimization model heuristics. A net profit margin of 15.22% and profit per unit of IDR 87,667 is remarkable, especially for MSMEs operating on thin margins. The sustained transportation expenses below 1.5% of revenue while achieving these figures underscores last-mile logistics cost-structure penalization for driving delivery routing efficiency.

Positioned within the broader context of other literature, this study broadens and reinforces past research. GA's effectiveness in solving VRPs was not in question. There was no mention of demand simulation monthly, MSME-focused limitations, or tailored cost modelling by industry. This study addresses the gap by implementing a GA on a constrained monthly planning cycle for a manufacturing-distribution MSME using realistic data inputs, thus providing methodological validation and practical relevance.

The findings offer actionable insights for MSME executives and public sector planners, in addition to theoretical contributions. Evolutionary algorithms, often limited to large-scale or high-tech endeavors, can be adapted into lightweight, operationally accessible tools for traditional sectors like footwear manufacturing. The tools can be integrated into routine decision-making processes if the technology is accompanied by user-friendly design and low maintenance needs. These contributions notwithstanding, the study comes with some limitations. The model intentionally adopts fixed transportation costs based on per-visit pricing commonly practiced by MSMEs in the studied region, though fuel price fluctuations warrant consideration in future iterations for dynamic cost modeling. The single-objective fitness function prioritizes profit maximization as the primary MSME concern yet lacks service-level reliability variables such as delivery time windows and carbon emissions tracking, which are increasingly relevant for sustainable logistics practices. Such constraints mark fruitful prospects for future research, including adding stochastic demand, multi-objective Pareto optimization, and hybridization with other algorithms like NSGA-II or Ant Colony Optimization (ACO) for better exploration. To conclude, this study validates the application of GA for distribution optimization in MSMEs and proves its ability to facilitate intricate strategic decisions even within tightly bounded, highly competitive contexts. The system developed in this work constitutes progress towards agile logistics planning within the scope of intelligent systems for resource-constrained enterprises because it is adaptable and can be practically implemented.

Conclusion

This study provides a practical and computationally efficient solution to using GA to optimize the monthly logistics distribution for MSMEs in the Indonesian footwear industry. The proposed model integrates real-world data such as demand variability, cost structures, and production limits. With this, the model can solve resource-constrained distribution planning problems with competing objectives. The results indicate that GA performs well in profit maximization with constraint satisfaction for the given problem and provides practical strategic recommendations. The algorithm consistently converged within a reasonable number of generations, achieving full capacity (100%) with utilization and servicing high-yield customers based on profitability rank rather than geography. The allocation strategy provided increased new margins of 15.22%, reduced transportation expenditure to less than 1.5% of revenues and remained feasible without incurring penalty costs. These results demonstrated the feasibility of applying GA to assist MSMEs' monthly logistics planning problem, constrained by production and logistics. In addition, the study aims to contribute to existing literature by employing GA in a context that is less highlighted, such as monthly distribution planning for a focused industry (footwear manufacturing) in a developing country. The model applies theoretical optimization in a more practical logistical context, creating a repeatable framework that can be scaled to other regions or industries with shared structural attributes.

Despite these contributions, this study has several limitations that might be considered for further research. To begin with, the demand for goods and transportation costs are currently fixed in the model. Moreover, fuel price fluctuation and market demands must be considered. Future versions could benefit from the assumption of stochastic or fuzzy demand models. Future research should transition toward multi-objective optimization frameworks, integrating environmental impact, customer satisfaction, and on-time delivery metrics alongside profitability. Implementing advanced algorithms such as NSGA-II or hybrid metaheuristics (e.g., GA-ACO) would enable Pareto-optimal solutions that better balance competing objectives. Finally, real-time deployment would allow the model to interface with the decision-enhancing system for MSME managers, significantly advancing practical implementation. Incorporating stochastic demand modeling and dynamic fuel pricing would enhance realism, while developing a real-time decision support interface could significantly improve practical adoption by MSME managers for day-to-day operational planning. As noted above, this study shows that GA can be an effective and flexible optimization tool for MSMEs trying to enhance their operational efficiency in the case of distribution systems. With further tailoring and contextual refinement, this approach has considerable promise for more diverse multi-dimensional supply chain and logistics optimization applications in developing countries.

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