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Optimizing business location for small and medium enterprises considering travel time uncertainty, natural disasters, and density population: a study case in Jakarta

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ABSTRACT

This study addresses the critical problem of identifying optimal business locations for small and medium enterprises (SMEs), a decision-making process by factors such as travel time uncertainty, natural disasters, and population density. Existing research in this area has not adequately addressed these complexities, leaving a knowledge gap that this study aims to fill. Our research employs two optimization methods, differential evolution (DE) and mixed integer programming (MIP), to maximize customer coverage. We present a comprehensive model that not only determines optimum and near-optimum business locations but also investigates the scalability of the algorithms with increasing facilities and their adaptability to different traffic scenarios. Key findings indicate that the DE algorithm, in particular, demonstrates superior coverage performance. This study contributes to the field by providing a robust and adaptable model for facility location problem-solving. The insights gained have practical applications for both academia and industry, aiding SMEs in making informed, strategic decisions about business location placement.

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1. INTRODUCTION

Strategic location selection is a critical determinant of success for Small and Medium Enterprises (SMEs) [1]–[3]. A well-chosen location can enhance business visibility, facilitate customer access, and positively impact operational costs [4], [5]. However, identifying the optimal business location is a complex endeavor, influenced by a multitude of factors, including travel time uncertainty [6]–[8], natural disasters [9]–[11], and population density [12]–[14].

Travel time uncertainty, characterized by factors such as traffic congestion, road conditions, and distance, significantly influences customer behavior, potentially leading customers to seek alternatives if they perceive the journey to a business as challenging or time-consuming [15], [16]. It highlights the importance of location selection for SMEs, prioritizing easy accessibility and reliable transportation routes. Research supports this, with studies by Berman *et al.* [6] examining the impact of traffic variations and special events on facility location, Johansson *et al.* [7] exploring the effects of uncertainty on vehicle platooning benefits, and Chen *et al*. [8] introducing a framework for evaluating urban accessibility that incorporates the reliability of travel times.

Natural disasters, such as floods, earthquakes, and storms, threaten SMEs by jeopardizing physical assets, disrupting operations, and potentially causing financial losses that could lead to temporary or permanent closure. Existing research acknowledges this risk. Ma *et al*. [9] emphasize the importance of strategic site selection for shelters, highlighting the need to incorporate uncertainty into disaster models. Additionally, other studies explore frameworks for disaster management and risk reduction, further emphasizing the need for SMEs to consider natural disaster risk during location selection [10], [11].

Population density, a measure of inhabitants per area, significantly influences business location decisions for SMEs. Densely populated regions offer a double-edged sword: a broader potential customer base, potentially leading to higher profits [12], but also intensified competition from other businesses [13], [14]. It highlights the importance of considering population density alongside other factors when selecting a strategic location.

This study addresses a research gap in understanding the combined influence of travel time uncertainty, natural disasters, and population density on the strategic location decisions of SMEs. It proposes a comprehensive model integrating these factors to assist SMEs in identifying optimal business locations. The novelty lies in its approach, incorporating linear programming (LP) and Metaheuristics. LP ensures an optimal solution but can be time-consuming, while metaheuristics provide a quicker, feasible solution.

This research is crucial as it offers SMEs a robust decision-making tool that considers multiple real-world factors, enhancing their strategic planning capabilities. SMEs can improve their operational efficiency, customer reach, and overall competitiveness by optimizing location decisions. Furthermore, the insights from this study could inform policy-making in support of SMEs, contributing to economic development and resilience in the face of uncertainties.

This study is structured in the following way: Section 2 explains research methods. The result and discussion are outlined in Section 3. Finally, Section 4 concludes the research

2. RESEARCH METHODS

This section will delve into the details of the proposed methodology. Fig. 1 illustrates the proposed methodology aimed at aiding SMEs in pinpointing the optimal business location.

2.1. Model formulation

Expected coverage problem (ECP) for facility location planning

The primary objective of the ECP model is to maximize the expected coverage of each demand point, taking into account the probability of each scenario [6]. In practical business applications, the theory of the coverage problem for facility location planning plays a crucial role. For instance, a retail business might leverage this model to strategically place its stores in a city, aiming to select locations that are easily accessible to a majority of its potential customers, thereby maximizing sales potential. Similarly, a logistics company might utilize this model to optimize the placement of its warehouses to minimize transportation costs and delivery times.

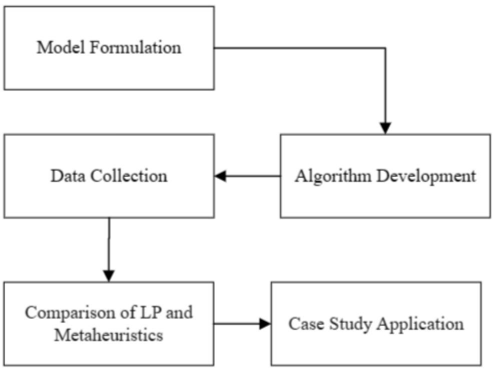

Fig. 1. The proposed approach

Formally, consider m facilities with coverage time T that need to be located on a directed network $G(N, A)$ with a set of nodes $N(|N| = n)$, each node $i \in N$ having a weight W_i, and a set of links $A(|A| = a)$. We will use $e \in G$ to represent a point that is either a node of G or belongs to the interior of some link. S scenarios represent the network uncertainty; we let l^k_{ij} be the travel time of link (i, j) in scenario k, where the link travel times for each scenario are assumed to be monotone, increasing the travel distance. For points $e, f \in G$, we let t^k_{ef} be the shortest travel time from e to f under scenario k. Facilities can be located at nodes or anywhere on links. Let $X \subset G$ be a location vector of m open facilities. Define $N^k_X = \{i|\, min_{x\epsilon X}\, t^k_{ix} \leq T\}$ as the set of nodes covered in scenario k by facilities in X, where T is the predefined time standard. Table I displays the

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notation of ECP. Then, ECP can be formulated as follows:

$$\text{maximize } z = \sum_{i=1}^{n}\sum_{k=1}^{S} W_i P_k y_{ik} \tag{1}$$

$$y_{ik} \le \sum_{j=1}^{\hat{n}} x_j I_{kij} \quad \text{for all } i \in 1,...,n; \quad k = 1,...,S \tag{2}$$

$$\sum_{j=1}^{\hat{n}} x_j = m \tag{3}$$

$$x_j = (0,1) \quad \text{for all } j = 1,...,\hat{n} \tag{4}$$

$$y_{ik} = (0,1) \quad \text{for all } i = 1,...,n; \quad k = 1,...,S \tag{5}$$

In this formulation, I_{kij} is a binary decision variable that equals 1 if a business facility located at critical point j covers node i in scenario k, and 0 otherwise. Essentially, it indicates whether a facility at a specific location can provide service to a particular demand point within the coverage time under the travel time conditions of a given scenario.

The binary decision variables x_j = 1 if a facility is located at critical point j and y_{ik} = 1 if node i is covered by some facility in scenario k. The objective function (1) is to maximise the expected coverage of the demand point by considering the probability of each scenario. Constraint (2) ensures that the demand point i will be covered by any facility at j in scenario k. Constraint (3) ensures that the number of facilities is limited to m. Constraints (4)-(5) are binary decision-making.

However, the mathematical model presented faces a challenge due to the non-linearity introduced by multiplying decision variables x_j and I_{kij} in Constraint (2). Linear models require variables to appear independently, not multiplied.

To address the issue of non-linearity, an additional decision variable is introduced. For instance, a new variable z_{ijk} represents the product of x_j and I_{kij}. Consequently, constraint 2 can be rewritten as follows:

$$y_{ik} \le \sum_{j=1}^{n} z_{ijk} \quad \text{for all } i = 1,\ldots,n \quad \text{and } k = 1,\ldots,S \tag{6}$$

This transformation ensures linearity because z_{ijk} simply reflects the product of the original variables without introducing additional multiplications. Essentially, z_{ijk} acts as a switch, being 1 only when both x_j and I_{kij} are 1 and 0; otherwise, preserving the original constraint's intent in a linear form.

The introduction of an additional decision variable z_{ijk} necessitates the inclusion of several supplementary constraints to ensure consistency between z_{ijk}, x_j, and I_{kij}. These additional constraints are as follows:

$$z_{ijk} \le x_j \quad \text{for all } i = 1,\ldots,n, \quad j = 1,\ldots,n, \text{ and, } k = 1,\ldots,S \tag{7}$$

$$z_{ijk} \le I_{kij} \quad \text{for all } i = 1,\ldots,n, \quad j = 1,\ldots,n, \text{ and, } k = 1,\ldots,S \tag{8}$$

$$z_{ijk} \ge x_j + I_{kij} - 1 \quad \text{for all } i = 1,\ldots,n, \quad j = 1,\ldots,n, \text{ and, } k = 1,\ldots,S \tag{9}$$

$$z_{ijk} = (0,1) \quad \text{for all } i = 1,...,n;\ j = 1,...,n';\quad k = 1,...,S \tag{10}$$

Constraints (7) and (8) ensure that z_{ijk} cannot be 1 unless both x_j, and I_{kij} are 1. Constraints (9) ensures that if both x_j and I_{kij} are 1, then z_{ijk} must be 1. Thus, z_{ijk} now represents the product of x_j and I_{kij}, but without rendering the model non-linear.

Population density and disaster-free locations

Two parameters are introduced to enhance the ECP model for selecting optimal SME locations. D_i represents population density at each location, with higher values receiving more weight due to a larger potential customer base. These density values are normalized (scaled between 0 and 1) using Equation (11) to prevent bias and facilitate interpretation. Normalization ensures all locations contribute equally regardless of their original density.

Conversely, B_j is a binary parameter indicating whether a location is free from natural disasters (1) or not (0). It ensures facilities are only placed in safe areas, mitigating business assets and operations risks.

$$D_i' = \frac{D_i}{\max(D)} \tag{11}$$

These modifications make the mathematical model more comprehensive and realistic for real-world applications. It now considers both population density and disaster risk in determining the optimal locations for facilities. Below is the updated LP of the coverage problem:

$$\text{maximize } z = \sum_{i=1}^{n}\sum_{k=1}^{S} D_i' W_i P_k y_{ik} \tag{12}$$

Constraints (6)-(10)
Constraints (3)-(5)

Assumptions of the developed ECP model

The developed ECP model incorporates several key features to address real-world complexities for SMEs. First, it acknowledges the uncertainty of travel times by considering various scenarios (e.g., regular traffic, congestion) and their likelihood of occurrence. It ensures that the chosen location remains accessible under different conditions.

Table 1. Notation

m	:	Number of business facilities
T	:	Coverage time for the business facilities
$G(N, A)$	:	Directed network with a set of nodes N and a set of links A
n	:	Number of nodes in the network
a	:	Number of links in the network
e	:	A point that is either a node of G or belongs to the interior of some link
S	:	Number of scenarios representing network uncertainty
t^k_{ef}	:	Shortest travel time from point e to point f under scenario k
X	:	Location vector of m open facilities
N^k_X	:	Set of nodes covered in scenario k by facilities in X
Di	:	Population density at node i
B_j	:	Binary parameter indicating if location j is free from natural disasters
I_{kij}	:	Binary parameter indicating if a facility located at critical point j covers node i in scenario k
x_j	:	Binary decision variable indicating if a business facility is located at critical point j
y_{ik}	:	Binary decision variable indicating if node i is covered by some facility in scenario k

Second, the model offers flexibility in location selection. Businesses are not restricted to specific points but can be situated anywhere along network links, allowing for strategic placement within a broader area. Finally, the model goes beyond traditional approaches by considering both population density and disaster risk as crucial factors influencing optimal location selection.

The modified ECP model with Di and Bj is transformed into a mixed integer programming (MIP) problem to achieve a more precise representation of the problem. MIP allows for both continuous and integer variables, making it suitable for facility location planning [17]. This formulated problem is then solved using a powerful solver like Gurobi, which is known for efficiently handling large-scale optimization. By comparing the MIP solution with results from metaheuristic methods, the study aims to identify the most effective approach for pinpointing the optimal location for SMEs.

2.2. Algorithm development

This study leverages a metaheuristic approach called differential evolution (DE) for solving the complex facility location problem. Metaheuristics provide general frameworks for developing algorithms to tackle challenging optimization issues [18], [19]. They are particularly useful when traditional methods struggle, offering good solutions within reasonable time frames [18].

DE, known for its simplicity and effectiveness, is a popular choice for complex optimization problems [20]. It utilizes a population-based approach, starting with a set of potential solutions and iteratively improving them by incorporating variations from randomly chosen members within the population. It enables DE to explore the solution space effectively and converge towards the optimal location.

The selection of DE over other algorithms like genetic algorithm (GA) or particle swarm optimization (PSO) is due to several factors. Firstly, DE excels at handling non-linear and multimodal functions, which are common in facility location problems [21]–[23]. Secondly, DE requires fewer control parameters compared to GA and PSO, making it easier to implement [23], [24]. Finally, studies have shown that DE can achieve better solutions with less computational effort [25].

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While DE is typically used for continuous problems, it can be adapted for discrete problems like facility location selection through discretization [26]. This process transforms the continuous solution space generated by DE into a discrete space with relevant options for facility placement [27]. This adaptation allows DE to effectively address the complexities involved in selecting optimal locations for SMEs.

The DE algorithm, as applied to the modified ECP model, involves a discretization process to handle the problem's discrete nature. Here is the algorithm where P is the population of potential solutions, X, A, B, C are vectors in P, D is the donor vector, U is the trial vector, F is a scaling factor for mutation. The modified ECP model's objective function determines a solution's fitness.

The DE algorithm employed in this study tackles the facility location problem through an iterative process. It starts by initializing a population of random solutions, each representing a potential configuration of facility placements. The algorithm then iterates until a stopping criterion is reached, such as a maximum number of iterations or achieving a high percentage (e.g., 95%) of the maximum possible demand coverage.

Within each iteration, the DE algorithm works on individual solutions in the population. It randomly selects three solutions and creates a new solution by combining them with variations. It injects diversity into the population. Next, using a thresholding technique, the algorithm transforms this continuous solution into a discrete one suitable for facility location selection.

The resulting solution is evaluated for feasibility (adherence to constraints) and effectiveness in covering demand points. If this new solution proves superior to the existing one, it replaces the older solution in the population. Finally, upon reaching the termination condition, the algorithm returns the best discrete solution identified as the optimal location for the SME.

2.3. Data collection

The data collection process for the modified ECP model involved collecting facility location and demand point information, including geographical coordinates, as shown in Table 2, over a period of four days. All the required data was readily available, so data collection did not take too long.

Ideally collected under non-congested conditions, travel time data is obtained from sources like Google Maps to ensure its reliability. This data is used to assess the accessibility of potential facility locations. The Google Maps API is used for geocoding and finding travel time, converting place names into precise geographical coordinates and calculating optimal routes between locations respectively. Table 3 displays the results of the travel time finding using Google Maps API.

Table 2. The snippet of geographical coordinates

Location	Latitude	Longitude
Cengkareng Barat	-6.1398647	106.7238102
Cengkareng Timur	-6.1409572	106.7353678
Duri Kosambi	-6.1704014	106.7201486
Kapuk	-6.1391425	106.7522077
Jelambar Baru	-6.1487012	106.7869928

Table 3. The snippet of travel time data

Location	Cengkareng Barat	Cengkareng Timur
Cengkareng Barat	0	1.541935
Cengkareng Timur	1.541935	0

The demand at each location is determined from the SMEs' sales data, reflecting the sales volume or demand at each location. The weight of demand at each location, W_i, is calculated by normalizing the sales volume, C_i, at each location by the total demand, as shown in Equation (13). Table 4 displays the snippet of demand data.

$$W_i = \frac{C_i}{\sum_{j=1}^{n} C_j} \tag{13}$$

Table 4. The snippet of demand data

Demand	Weight
15	0.00436
15	0.00436
16	0.004651
31	0.009012

Population density data at each demand point or region is collected from sources like population censuses or government data to ensure reliability. This data, comprising the number of individuals in each region (P_i) and area measurements (A_i), is used to calculate population density, as shown in Equation (14) [28], [29]. The calculated population density is then used in the model's objective function to weigh the importance of covering each demand point. Table 5 displays the snippet of density data.

$$D_i = \frac{P_i}{A_i} \tag{14}$$

Table 5. The snippet of density data

Location	Population (inhabitants)	Area (km2)	Density (inhabitants/km2)
Cengkareng Barat	74,922	3.61	20,754
Cengkareng Timur	90,832	4.51	20,140
Duri Kosambi	86,358	5.91	20,754
Kapuk	154,813	5.63	27,498

Then, information about the risk of natural disasters at each potential facility location is also collected. This binary parameter indicates whether a location is free from natural disasters. Data on flood zones, for instance, can be obtained from government sources, such as the provincial government of Jakarta, to identify locations free from the risk of flooding [30]. Table 6 displays the snippet of prone-disaster data.

Table 6. The snippet of prone-disaster data

Location	Status
Cengkareng Barat	1
Cengkareng Timur	1
Duri Kosambi	1
Kapuk	1
Kedaung Kali Angke	0
Rawa Buaya	1

The study incorporates four scenarios, each with a distinct probability and impact on travel times. The 'Typical Scenario' (Probability = 0.5) represents normal conditions with no floods and shortest travel times. The 'Light Congestion' scenario (Probability = 0.2) accounts for light traffic, leading to a 10% increase in travel times. The 'Moderate Congestion' scenario (Probability = 0.2) assumes moderate traffic, resulting in a 25% increase in travel times. Lastly, the 'Extreme Scenario' (Probability = 0.1) considers severe floods, causing a substantial 50% increase in travel times. These scenarios ensure that the model provides a robust solution under various conditions, including extreme flood scenarios.

2.4. Comparison of LP and metaheuristics

In the context of the modified ECP model, the comparative analysis between LP and the metaheuristic method, DE, hinges on two pivotal aspects, the coverage value (fitness function) and processing time. A higher coverage value indicates a more desirable or optimal solution. At the same time, a shorter processing time is generally preferred as it indicates that the algorithm can find a solution more quickly, which is particularly important in real-time or time-sensitive applications.

2.5. Case study application

A case study at a Jakarta bakery aimed to maximize demand coverage across 261 sub-districts by opening up to five branches, avoiding flood-prone areas. Travel times were determined using Google Maps during non-congested periods, with a travel time coverage set at 10 minutes. Programs using the DE algorithm and MIP were developed, with inputs including facility locations, demand point information, demand weights, population density data, natural disaster-free locations, and travel time data.

The evaluation of the algorithms is based on two benchmarks: coverage level, also known as the fitness function and processing time. These benchmarks provide a robust measure of the effectiveness and efficiency of the algorithms. The parameters for the study are systematically varied. The number of facilities was adjusted from 1 to 5, and four scenarios with different probabilities were considered. In the sensitivity analysis, these probabilities were adjusted to more extreme values to test the robustness of the algorithms.

The termination criteria for the algorithms were carefully chosen. The MIP algorithm stops when it finds the optimal solution, while the DE algorithm stops when the best fitness reaches at least 95% of the maximum possible demand coverage. These criteria ensure that the algorithms stop when a satisfactory solution is found, optimizing computational resources.

Finally, the study included two sets of trials. The first set was a standard test, and the second set was a sensitivity analysis. In each trial, the DE algorithm was run 30 times, and the results were compared with the output of the MIP program, which was run once due to its deterministic nature.

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This approach ensures a thorough and rigorous evaluation of the algorithms, providing reliable and statistically valid results.

The programs' expected output is the optimal facility locations, assisting SMEs in strategic location decisions. Experiments were conducted on a desktop PC with an AMD Ryzen 5 5500U CPU and six physical cores, with specific parameters for the DE and an optimality tolerance of 1e-7 for the MIP solver.

3. RESULTS AND DISCUSSION

3.1. Results of computation

Table 7 provides a comparative performance analysis between the DE algorithm and MIP for a facility location problem, considering the number of facilities (m), coverage, and processing time. Coverage measures the proportion of demand met by the facilities. DE provides average, maximum, and minimum coverage values, while MIP, a deterministic method, provides a single coverage value.

As the number of facilities increases, both DE and MIP algorithms improve their coverage. However, DE consistently achieves higher coverage at the cost of longer processing times, particularly due to its termination condition that stops the algorithm when the best fitness reaches at least 95% of the maximum possible demand coverage. On the other hand, MIP systematically seeks an optimal solution and stops when it has either found the optimal solution or exhausted the solution space.

The DE algorithm's performance in finding the best coverage or fitness value improves consistently as m increases from 1 to 5 (Fig. 2). Each increment in m leads to rapid convergence towards the optimal solution initially, followed by plateaus indicating the algorithm has likely converged to a near-optimal solution. The pattern of rapid improvement followed by plateaus as m increases underscores the robustness and efficiency of the DE algorithm in solving the facility location problem across different m values.

Table 8 presents a comparative analysis of the coverage achieved by the DE and MIP algorithms under different traffic scenarios and for varying numbers of facilities. The DE algorithm consistently outperforms MIP regarding total coverage, indicating its superior effectiveness in maximizing demand coverage. As the number of facilities increases, both algorithms show improved coverage, but DE exhibits a more pronounced improvement.

Coverage varies under different traffic scenarios, emphasizing the need to consider varying traffic conditions in facility location problems. The analysis suggests that DE can effectively utilize additional facilities to increase coverage. It underscores the robustness of the DE algorithm in adapting to different problem scales and traffic conditions, making it a potentially more effective choice for solving facility location problems.

The sensitivity analysis is also performed to understand how the variation in the output of a model can be attributed to different sources of variation in its inputs [31], [32]. In this context, a sensitivity analysis is performed to verify the impact of different probabilities on the coverage and number of facilities. It involves adjusting the probabilities of different scenarios and observing the effect on the model's output. The extreme scenario is set as the highest probability (50%), followed by the typical scenario (20%), the moderate congestion scenario (20%), and the light congestion scenario (10%). By doing this, the analysis can help determine how changes in traffic conditions might affect the optimal number and location of facilities, thereby aiding strategic decision-making in facility location planning.

Table 9 presents the sensitivity analysis results where the extreme scenario has the highest probability. The table shows the coverage achieved by DE and MIP algorithms under different traffic scenarios and for varying numbers of facilities. When the probability of the extreme scenario increases, both algorithms show a decrease in total coverage. It suggests that both DE and MIP are sensitive to extreme traffic conditions, and their performance may degrade under such conditions. However, the DE algorithm consistently outperforms the MIP algorithm in terms of total coverage, indicating its superior effectiveness in maximizing demand coverage under varying traffic conditions.

3.2. Discussion and research implications

The study found that the DE algorithm outperforms the MIP in various scenarios due to its ability to explore and adapt to complex problem landscapes. DE's population-based nature allows for extensive navigation of the solution space, making it suitable for problems with non-linearity, discontinuity, and multiple local optimal.

Contrary to conventional wisdom, DE

Table 7. A comparative performance analysis between the DE algorithm and MIP

m	DE algorithm					MIP	
	Coverage				Avrg. Processing (seconds)	Coverage	Processing (seconds)
	Average	Max	Min	Std.			
1	0.57	0.57	0.57	0.000	60.80	0.28	36.88
2	0.72	0.72	0.71	0.003	74.70	0.36	41.19
3	0.85	0.85	0.85	0.000	82.90	0.42	37.29
4	0.91	0.92	0.91	0.005	67.80	0.45	36.81
5	0.95	0.96	0.95	0.004	17.80	0.47	38.45

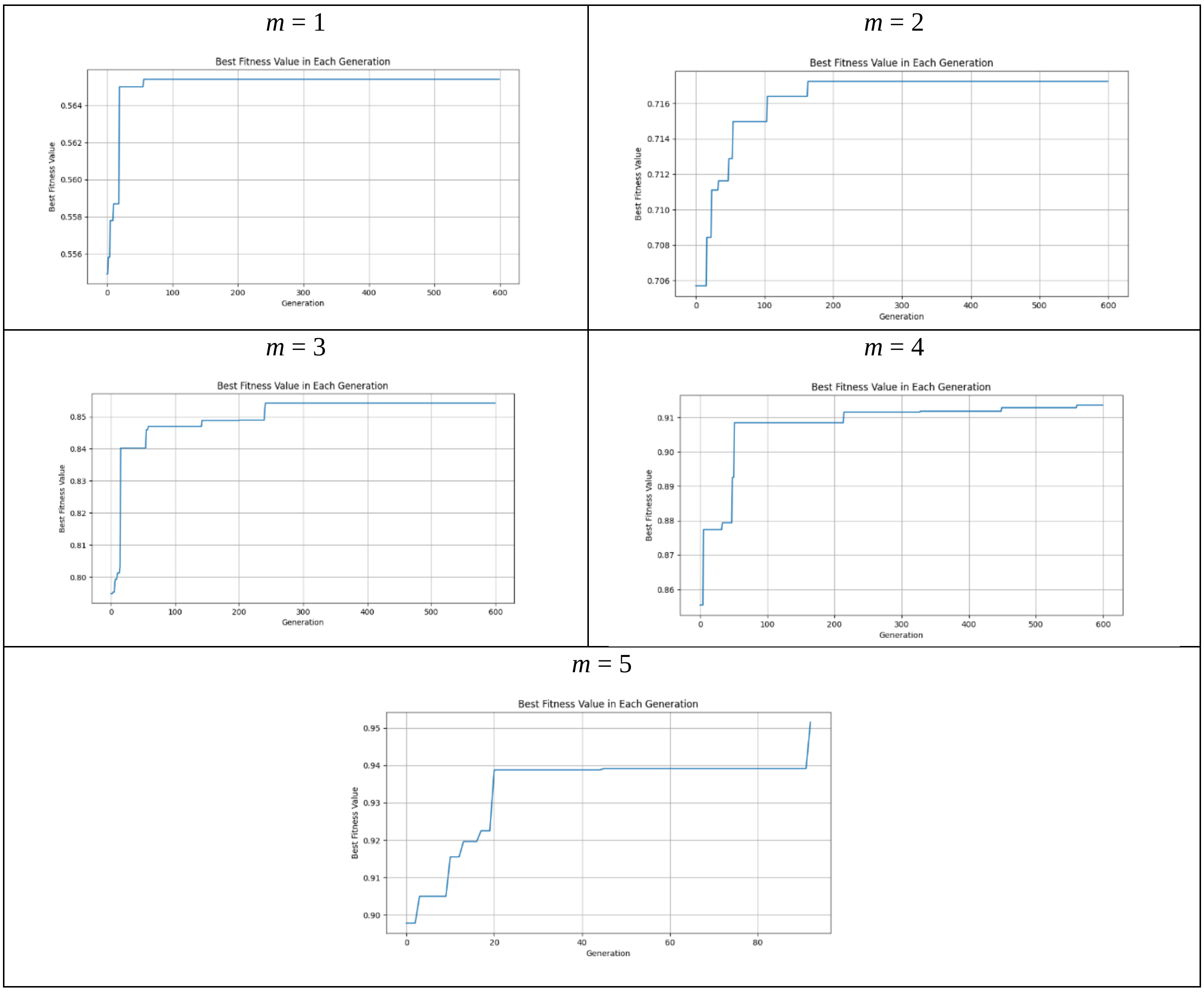

Fig. 2. Best fitness value in each generation

exhibited longer processing times than MIP. It is due to DE's iterative evolution of solutions over multiple generations until a termination condition is met, which in this study was set at 95% of the maximum possible demand coverage.

MIP, on the other hand, uses a systematic branch-and-bound approach to explore the solution space. Its efficiency depends on the solution space's size and the bounding operations' effectiveness. In this study, MIP benefited from a smaller solution space and effective bounding, leading to quicker discovery of the optimal solution.

Another significant finding is the DE algorithm's performance under different traffic scenarios. The algorithm's adaptability is crucial for a bakery business, as customer footfall can vary significantly depending on factors such as

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time of day, day of the week, and season. By using the DE algorithm, bakery businesses can plan their operations to cater to these varying conditions, ensuring optimal service delivery and customer satisfaction.

The DE algorithm used in this research to determine the optimal business location for a bakery SMEs have several advantages and disadvantages. On the positive side, DE is a powerful and efficient global optimization algorithm capable of handling complex, non-linear, and multimodal problems. It is particularly effective in dealing with continuous spaces and can find global optima in large search spaces, making it suitable for our location optimization problem. Furthermore, DE's simplicity and ease of implementation are other advantages, as it requires fewer control parameters than other algorithms.

On the downside, DE can sometimes converge slowly, especially for high-dimensional problems, which could be a limitation in scenarios where quick solutions are needed. Additionally, while DE is robust in handling a wide range of problems, it may not always provide the best solution for certain specific or constrained problems compared to specialized algorithms. Lastly, DE, like other evolutionary algorithms, may require a significant number of function evaluations to reach the global optimum, which could be computationally expensive for very large problems. However, in the context of our study, the benefits of using DE outweigh these limitations.

Table 8. A comparative of the coverage achieved by the DE and MIP under different scenarios and for varying numbers of facilities

		Coverage in the scenario				**Total**
Method	***m***	**Typical**	**Light**	**Moderate**	**Extreme**	
DE	1	0.29	0.11	0.11	0.06	0.57
MIP	1	0.14	0.06	0.06	0.03	0.28
DE	2	0.36	0.14	0.14	0.07	0.72
MIP	2	0.18	0.07	0.07	0.04	0.36
DE	3	0.43	0.17	0.17	0.09	0.85
MIP	3	0.21	0.08	0.08	0.04	0.42
DE	4	0.46	0.18	0.18	0.09	0.91
MIP	4	0.23	0.09	0.09	0.05	0.45
DE	5	0.48	0.19	0.19	0.10	0.95
MIP	5	0.24	0.09	0.09	0.05	0.47

Table 9. A comparative of the coverage achieved by the DE and MIP under different scenarios and for varying numbers of facilities

Method	***m***	**Coverage in the scenario**				**Total**
		Typical	**Light**	**Moderate**	**Extreme**	
DE	1	0.12	0.11	0.05	0.20	0.48
MIP	1	0.05	0.05	0.02	0.12	0.24
DE	2	0.15	0.14	0.05	0.27	0.61
MIP	2	0.06	0.06	0.03	0.16	0.32
DE	3	0.17	0.16	0.07	0.34	0.74
MIP	3	0.08	0.08	0.04	0.19	0.38
DE	4	0.18	0.17	0.08	0.38	0.81
MIP	4	0.08	0.08	0.04	0.21	0.41
DE	5	0.19	0.19	0.09	0.43	0.90
MIP	5	0.09	0.09	0.05	0.23	0.45

The decision on the number of facilities to open and their locations has significant implications for the bakery store in Jakarta. The choice directly impacts the store's ability to maximize demand coverage across the 261 sub-districts.

If the store opts for a smaller number of facilities, such as 1 or 2, the coverage is lower. It means the store may be unable to serve a large proportion of the demand, potentially missing out on customers and sales. On the other hand, if the store decides to open a larger number of facilities, such as 4 or 5, the coverage significantly improves. This means the store can serve a larger proportion of the demand, potentially leading to higher sales and profits. Therefore, the store must balance the trade-off between maximizing coverage (and potentially sales) and the number of business facilities.

The optimum placement of business facilities and coverage areas is illustrated in Fig. 3. Each location is marked with a pop-up on the map, and

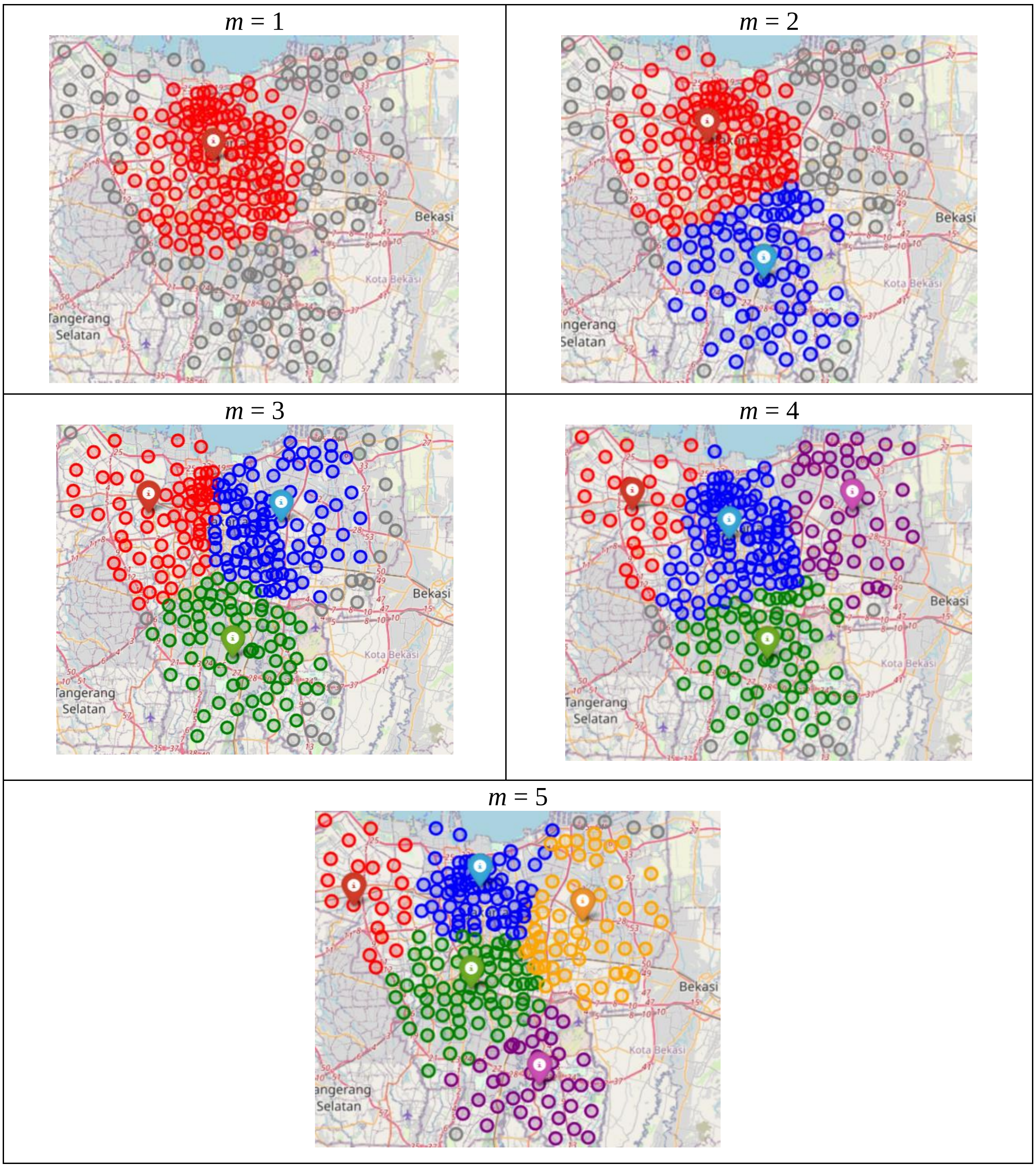

Fig. 3. A visual representation of the optimum facility locations with different number of business facilities

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the area covered by each location is color-coded to match the corresponding pop-up. These locations are considered optimal based on several factors. Firstly, they offer reasonable travel times between the facility and the customer locations, ensuring accessibility. Secondly, these areas are free from flood risks, providing a safer location and ensuring accessibility. Secondly, these areas are free from flood risks, providing a safer environment for business operations. Lastly, these areas are densely populated, offering a larger potential customer base for the businesses.

While this study provides valuable insights into the potential coverage that can be achieved by varying the number of facilities, it does not incorporate the cost of opening and operating these facilities. Therefore, it cannot definitively determine the optimal number of business facilities. Costs, including rent, utilities, staffing, and inventory, among others, can significantly impact the profitability of each facility. A facility that increases coverage but operates at a loss would not benefit the business.

Future research could incorporate cost considerations into the model to address this limitation. It could be achieved by assigning a cost to each potential facility location and including a budget constraint in the model. The objective would then be to maximize coverage subject to this budget constraint. It would provide a more realistic and applicable model for businesses.

In the meantime, businesses could use the findings of this study as a starting point. They could first use the DE algorithm to identify potential facility locations that maximize coverage. Then, they could evaluate the costs associated with each location and make decisions based on coverage and cost. While not as efficient as a fully integrated model, this approach could still lead to more informed and effective decisions.

The scalability of DE and MIP algorithms is a crucial aspect of their utility. As an SME bakery business expands, it may open new outlets, offer new products, or serve new markets. These changes increase the complexity of the location placement problem. However, the scalability of the DE and MIP algorithms ensures they can handle this increased complexity. They can manage a larger number of variables and constraints while still providing effective solutions. As the business grows, algorithms remain useful tools for decision-making.

The adaptability of the algorithms is another key feature. In the real world, conditions change. Travel times can vary due to road works or traffic congestion. Population density may change as people move in or out of an area. The risk of disasters such as floods or earthquakes may increase or decrease over time. The DE and MIP algorithms can adapt to these changes. They can incorporate new data, adjust to new conditions, and respond to changes in the problem parameters. This adaptability allows the algorithms to provide up-to-date and relevant solutions, helping businesses to make informed decisions about location placement. SMEs can practically apply these insights to optimize their operations, improve their resilience to uncertainties, and ultimately enhance their competitiveness in the market.

This research significantly advances facility location problem-solving, particularly for bakery businesses. It provides a comprehensive comparison of the DE and MIP algorithms, introducing performance metrics such as coverage and processing time. The study also explores the impact of the number of facilities and different traffic scenarios on the algorithms' performance. Additionally, the consideration of different traffic scenarios in the analysis acknowledges the dynamic nature of customer demand, making this research highly relevant to real-world applications. Most importantly, it applies these findings to the development of a bakery business to a real-world context, demonstrating the practical relevance of these algorithms.

4. CONCLUSION

This study has provided significant insights into the application of differential evolution (DE) and mixed integer programming (MIP) algorithms for solving optimal business location problems, particularly for SME bakeries. The research highlighted the impact of the number of facilities on the algorithms' performance and underscored the need for adaptable solutions in the face of varying traffic scenarios.

The unique contribution of this study lies in its practical application to real-world contexts, demonstrating the relevance and applicability of these algorithms in aiding SMEs in making informed location decisions. However, it is important to acknowledge that while the DE algorithm provides higher coverage, it does not incorporate cost considerations, a crucial factor in determining optimal business locations.

This limitation points to potential areas for future research. There is a need for further investigation that incorporates cost considerations to provide a more comprehensive decision-making tool for businesses. It would help them balance coverage and profitability, which is important for sustainable growth and success. Thus, the findings of this study serve as a stepping stone towards more holistic and practical solutions for facility location problems

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