Models and Heuristic Algorithms for Solving Discrete Location Problems of Temporary Disposal Places in Palembang City

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Abstract— **The discrete location problem has given more attention to operations research as the prevalent location-allocation problem in recent years. Discrete location problems have three main classifications: covering-based, median-based, and some different problems. An open facility location must cover demand in terms of range or travelled period in covering-based problems. The prospective site must cover all request points at the network centre in median-based problems. These problem categories are suitable for determining the public facility's location. There are very few literature reviews and models related to location-allocation theory. This paper aims to present detailed calculations or numerical methods computations and an overview of the studies, types, models, and previous researchers' methods to solve discrete location problems. We describes the set covering location problems, maximal covering location problems, p-center location problems, p-median location problems, and fixed charge facility locations problems. This paper also briefly explains several heuristic algorithms to solve discrete location problems, such as genetic algorithm, particle swamp optimization, and greedy reduction algorithm. We implemented the model and algorithm to determine the optimal temporary disposal places in Palembang City. The map of optimal temporary disposal places as the solution of the model was served in this paper.**

Index Terms— **discrete location problems, covering-based problems, median-based problems, heuristic algorithms**

I. Introduction

OPERATIONS research is a scientific method or qualitative decision-making approach that determines the optimum decision under limited resource constraints. The mathematical model is at the core of operations research and solves the problem using an algorithm or programmable procedures. Mathematical programming models widely used are linear programming (LP), integer linear programming (ILP), inventory, dynamic programming (DP), non-linear programming (NLP), network analysis, and stochastic programming (SP). Deterministic problems use these models. The location determination problems or facility location problems (FLP) also require a mathematical model to solve them. The solutions to these problems are to place facilities that can optimize services, cover the request points, distribute goods, optimize distances, transportation costs, or several other parameters.

One of the optimization problems is determining the optimal facility location. Location is a place to serve or provide facilities for the community to meet daily human needs. Public facilities are always related to community service to meet the economy and government's life needs. Sufficient conditions can increase the community's welfare without discriminating against the social level of the community [1]. Private and public sectors need to optimize the location procedures. Because of these location problem interpretations, not one but many problems exist, and each variation alters the mathematical character problem. Thus, various approaches solve location problems. Each is designed to meet the specifications of the particular interpretation problem.

FLP is divided into continuous location problems (CLP) and discrete location problems (DLP). If the number of prospective facility locations is limited, the problem is categorized as DLP. On the other hand, if the open facility can be placed in some continuous places, it is called the CLP. Previous FLP research has been done by [2]–[8]. This survey focuses on DLP, selecting the best location for facilities from a set of possible sites to minimize total costs while still satisfying consumer demand. DLP can be classified into models with each property to know the fit algorithm to solve the problems.

Previous studies on location determination have been carried out. However, they discussed determining the location using exact or heuristic algorithms without mentioning the model. They showed some numerical processes and detailed computation by using those algorithms. There have been limited studies concerned with the types and model formulation of DLP. Each problem will have different models and methods, so we explained the classes and models of discrete facility location (DFL). Each model has specific characteristics, especially in the objective function. The advantage of the survey in this paper is as a preliminary study

Manuscript received September 10, 2021; revised April 23, 2021. This work was supported by the scholarship of Mathematics and Natural Sciences Doctoral Study, Universitas Sriwijaya, Indonesia (Grant No. 0112/UN9/SK.BUK.KP/2021).

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in research on set covering problems, especially DFL, to develop advanced models further and propose new solving methods. Therefore, this paper briefly reviews the types, general model of DLP, and some algorithms proposed by earlier researchers.

The rest of this paper is arranged as follows. Section 2 presents the literature review of DLP, such as problem type, review of results, and the proposed methods. Section 3 briefly explains the classification of models in DLP, their characteristics, and some heuristic algorithms to solve the problem. Section 4 shows the numerical experiments for finding the optimal temporary disposal sites and the optimal mapping of DLP. Some conclusions are drawn in section 5.

II. Literature Review

The DLP broadly consists of two scopes. First, some open facilities are given, and the objective is to cover the maximum demand point. Second, this problem intends to reduce the number of opened facility locations but cover all customers within the maximum distance. This paper discusses the DFL, consisting of feasible facility locations and a limited group of demand points or requests.

The research on FLP has been improved fast for many years. Most researchers discussed and developed the methods or algorithms for the FLP without explaining the general model briefly. They designed and applied the classical, heuristics, semi-heuristics, and metaheuristics methods. Some researchers also reviewed articles. Paul and Hariharan [9] determined the location and capacities of stockpile sites using two delays and a generic model. Basu *et al.* [10] reviewed metaheuristic applications for finding different versions and models of the DLP. Javid *et al*. [2] reviewed and surveyed healthcare facility locations. Ghasemi and Razzazi [11] generalized the bin packing and the unit covering problem and called them the first-fit algorithm.

Some researchers have developed and modified the algorithms for solving the more significance of FLP. Fischetti *et al.* [12] solved a large-scale facility location by redesigning benders decomposition. Yadav *et al.* [13] formulated the FLP model for managing municipal solid waste in uncertain environments. They used a mathematical programming language called AMPL with KNITRO as a solver of the model. Xie [6] developed the multi gravity method to locate the logistics facilities and mapped them by Geographic Information Systems.

Furthermore, Martins de Sá *et al*. [14] applied the Benders Decomposition technique to solve a location problem. Kinay *et al.* [3] investigated multi-criteria modeling frameworks for solving discrete stochastic FLP with single sourcing. Corberán *et al.* [15] presented compact FLP models and improved them with valid inequalities separated in a branch-and-cut method. We also summarized some previous research about location-allocation problems. A brief table containing a summary study of DLP, which consists of the problem type, review of results, and proposed methods, can be seen in Table I.

TABLE I
DISCRETE LOCATION PROBLEMS

References	Problem Type	Review of Results	Proposed Methods
Javid *et al*. [2]	Healthcare facility location (HFL)	Gave the survey of HFL and its application	Did not propose any methods
Kinay *et al*. [3]	Capacitated DFL problem	Applied stochastic shelter site location problem and tested the models using uncertainty and multiple objectives	Rawlsian approach, vectorial optimization, and goal programming
Tamir [4]	Multi-facility location problem	Solved the p-facility k-centrum problem on path and tree graphs	Polynomial-time algorithms
Wolf [5]	Location models and covering metrics	Explained history, applications, and advancements of location covering models	Did not propose any methods
Paul and Hariharan [9]	Location-allocation problem	Applied the model for hurricanes and earthquakes	Mixed-integer programming models
Xie [6]	Logistics facilities location	Designed a multi centre of gravity logistics location algorithm based on Geographic Information Systems	Multi centre of gravity method
Ye and Kim [7]	Healthcare facility location problem	Applied the proposed algorithm to evaluate prospective facility sites fully, considered service capabilities, and demonstrated the integration of GIS	A network-based covering location problem
Zhang *et al*. [8]	Emergency service facilities location problem	Formulized the uncertain location set covering model and illustrated by a case study	Three uncertain covering models
Basu *et al.* [10]	Discrete facility location problem	Provided a detailed review of metaheuristic applications on DFL problems	Genetic algorithm, tabu search, and particle swarm optimization
Ghasemi and Razzazi [11]	Capacitated unit covering problem	The problem was not approximable within a factor better than 1.5	First-fit algorithm
Fischetti and Monaci [16]	Large-scale facility location	Benders decomposition allowed for a significant boost in the performance of a MIP solver	Benders decomposition

Yadav *et al.* [13]	Facility location problem in the municipal solid waste management system	The developed model selects five economically best locations out of ten potential locations	Fuzzy mathematical programming and grey programming
Martins de Sa *et al.* [14]	Incomplete hub location problem	Focused on multiple allocation incomplete hub location problem	Benders decomposition method
Corberan *et al.* [15]	Discrete facility location problem	Presented compact models which are tested with several hundred instances	Mixed-integer mathematical programming
Du *et al.* [17]	p-CLP	The proposed methods perform the best solution	A linear reformulation, benders dual cutting plane method, and a column and constraint generation method
Silva and Ramalho [18]	SCP	Applied a non-hybrid ant colony optimization and adopted a more accurate experimental evaluation method	Ant colony optimization
Iwamura *et al.* [19]	SCP	Opened a source program written in C to generate an input data set for the set covering problem	Open C source program
Lust and Tuyttens [20]	Bi-objective SCP	Proposed a new heuristic method to generate a good approximation of the Pareto efficient solutions	Two-phase Pareto local search
Pereira and Averbakh [21]	Robust SCP	The approach was recommended for problems that cannot be solved to optimality by exact algorithms	Benders decomposition, branch and cut
Crawford *et al.* [22]	SCP	The binary cat swarm algorithm produced competitive results solving a portfolio of SCP from the OR-Library	Cat swarm optimization
Octarina *et al.* [23]	SCP	Implemented SCP in solving CSP	Branch and bound
Al-Shihabi *et al.* [24]	SCP	The proposed algorithm can be considered the new state-of-the-art meta-heuristic to solve the SCP	Improved hybrid algorithm
Weerasena *et al.* [25]	Multi-objective SCP	The new algorithm executed best on some instances	Heuristic algorithm
Astorga *et al.* [26]	SCP	The approach has proved to be very effective in the parametrization of the metaheuristic responsible for resolving the problem	A meta-optimization approach
Sitepu *et al.* [27]	SCP in health facility location	Optimized the number and location of emergency installations in Palembang	Branch and bound
Octarina *et al.* [28]	SCP	Implemented GRASP in SCP to find the optimal pattern	GRASP
Davari *et al.* [29]	MCLP	The proposed method finds solutions with objective values no worse than 1.35% below the optimal solution	Fuzzy simulation and simulated annealing
Kim [30]	Set multi-cover problem	Presented a new method with random selection rules for the partial set multicover problem	Greedy heuristic
Gazani *et al.* [31]	Capacitated MCLP	The heuristic method is capable of producing optimal solutions in a rational execution time	Metaheuristic approach and GA
Cordeau *et al.* [32]	MCLP	Can cover the larger number of customers	Benders decomposition
Amarilies *et al.* [33]	MCLP	Implemented the new algorithm to find the optimal trashcan location	Greedy heuristics
Sandoval *et al.* [34]	p-CLP	The proposed algorithm performs significantly faster than the best-known exact solution method for this model	Sandoval–Díaz–Ríos algorithm
Irawan *et al.* [35]	Bi-objective capacitated p-median problem	Developed a mathematical model using ILP to determine the optimal location of open facilities with their optimal capacity	Compromise programming with an exact method and with a variable neighbourhood search
Mokhtar *et al.* [36]	p-hub median problem	Proposed a mathematical formulation and developed a modified benders decomposition method for solving hub-location problems	Modified benders decomposition method
Romero *et al.* [37]	p-median problem	Applied the proposed approach to get a good solution to the p-median problem	Tabu search algorithm
Lai *et al.* [38]	Max-mean dispersion problem	Investigated the two-hybrid evolutionary algorithms incorporating tabu search for solving the generalized max-mean dispersion problem	Two hybrids evolutionary algorithms/tabu search approaches

III. Results and Discussion

DLP are divided into three groups:

a. Covering-based problems (CBP) consist of set covering location problems (SCLP), maximal covering location problems (MCLP), and p-center location problems (p-CLP).
b. Median-based problems (MBP) consist of p-median location problems (p-MLP) and fixed charge facility locations problems (FCFLP).
c. Some different problems such as maximum dispersion, p-dispersion, and MNS location problems.

A. CBP

The main objective of these problems is to fulfill the service and satisfaction. The CBP ensured that the request location must cover a specific range or traveled period from the facilities that serve it. There are three fundamental CBP: SCLP, MCLP, and p-CLP.

1) SCLP

The SCLP is a related part of ILP in optimization, which concerns selecting the location-allocation, the best alternative, and aims to minimize those factors that affect the constraints model. Application of SCLP in daily life includes determining vehicle routes, garbage transportation, choosing vehicles to pick up passengers, buses at bus stops, airplane crew scheduling, resource allocation, etc.

Previous research on the SCLP has been carried out. Silva and Ramalho [16] applied the ant systems to solve the SCLP. Because of the large data set, Iwamura *et al.* [17] developed a program to generate the benchmark data set for solving the SCLP. Lust and Tuyttens [18] used a two-phase Pareto local method to solve the bi-objective SCLP. Finally, Pereira and Averbakh [19] studied the SCLP with uncertain cost, called the robust SCLP with interval data. They compared several heuristic methods to the problems.

Some applications of the heuristic method to solve SCLP are developing. Al-Shihabi *et al.* [20] improved a hybrid method to solve the SCLP, and Crawford *et al.* [21] used a cat swarm optimization algorithm to solve SCLP. The cat swarm algorithm works to follow the behavior of discrete cats and is known as a recent swarm metaheuristic technique. They applied the algorithm to many practical applications. Weerasena *et al.* [22] proposed an algorithm that used a branching technique on a tree structure and developed the node exploration for the multi-objective SCLP.

On the other hand, Astorga *et al.* [23] created a meta-optimization method to resolve the SCLP. For the application, Sitepu *et al.* [24] formulated the SCLP models to optimize the emergency unit location of the hospital in Palembang. They found six emergency unit locations that can serve eight sub-districts of Palembang City.

Other applications of the SCLP model are in the cutting stock problem (CSP). Octarina *et al*. [25] formulated the set covering problem (SCP) model to solve the multiple CSP. The model showed the efficient usage of stocks. In the same year, Octarina *et al*. [26] applied the greedy randomized adaptive search procedure (GRASP) in formulating the SCP model. The method can give different patterns but still yield the trim loss.

The SCLP aims to minimize the number of facilities built or the total fees of locations that can still fulfill the request level coverage. This issue determines the number and facility locations to cover all request points within a specified range or traveled period from the open facilities which serve customers.

The formulation of SCLP is:

$$Z_{SCLP} = \min \sum_{j \in J} f_j x_j \tag{1}$$

Subject to

$$\sum_{j \in N_i} x_j \geq 1, \qquad i \in I \tag{2}$$

$$x_j \in \{0,1\} \tag{3}$$

Some notations that are used in the SCLP modeling:

Z_{SCLP} = Objective function of the SCLP model.
J = The prospective locations.
f_j = The settled fees of locating at the prospective location $j \in J$.
$x_j = \begin{cases} 1, & \text{if a facility is established at prospective location } j; \\ 0, & \text{otherwise.} \end{cases}$
I = The request points.
N_i = All prospective locations $i \in I$ $(N_i = \{j \in J: d_{ij} \leq D_i\})$.
d_{ij} = The range or travel period from request point i to prospective location j.
D_i = The maximum cover range or travel period from request area $i \in I$.

Eq (1) is the objective function. It minimizes the facility location's cost required to cover all request points. Constraint (2) ensures that the solution must cover each request point, and Constraint (3) is a binary integer constraint.

2) MCLP

The MCLP differentiates vertices with tremendous and small requests by assigning a request level to each point. This problem allocates the p facility's location to maximize the request covered by the maximum coverage distance D_i. Davari *et al.* [27] used simulated annealing (SA) and a hybrid algorithm of fuzzy simulation to solve Fuzzy MCLP. The results showed a good performance. The objective values of the proposed SA were better than 1.35% below the optimal solution. Kim [28] solved the multicover problem in a partial set and used a minimum *k* direction finder to cover the likely transmitter positions.

Other research for large-scale MCLP was developing. Cordeau *et al.* [29] applied Benders Decomposition to solve massive scale partial SCP dan MCLP. Amarilies *et al.* [30] used Greedy Heuristic to solve MCLP in finding the optimal trashcan location, and Gazani *et al*. [31] developed a meta-heuristic approach and a constructive heuristic method to solve the capacitated MCLP with heterogeneous facilities and vehicles. They applied a genetic algorithm (GA) to construct the technique.

The MCLP model is as follows.

$$Z_{MCLP} = \max \sum_{i \in I} w_i z_i \quad (4)$$

Subject to

$$\sum_{j \in J} x_j = p \quad (5)$$

$$z_i \leq \sum_{j \in N_i} x_j \quad (6)$$

$$z_i \in \{0,1\} \quad (7)$$

$$x_j \in \{0,1\} \quad (8)$$

Some notations that are used in the MCLP modeling:

Z_{MCLP} = Objective function of MCLP model

w_i = The number of request at area $i \in I$.

$z_i = \begin{cases} 1, \text{if the request area } i \in I \text{ is covered;} \\ 0, \text{otherwise.} \end{cases}$

p = The number of prospective locations will be built.

The objective function (4) aims to maximize the coverage of request points or areas. Constraint (5) located p facilities in the area. In addition, Constraint (6) shows that open facilities only cover the request point. The last two constraints, Constraint (7) and Constraint (8) offer binary integer solutions.

3) p-CLP

The third type of CBP is p-CLP. This problem finds the minimum of the maximum range or travel period of allocated areas and facilities, where the facilities must cover each request point. A request point is assigned to the opened closest facility when the facility is out of capacity. The p-CLP is a type of min-max problem. It is also a location-allocation problem as long as this problem requires simultaneous location and allocation from the request point to the facility. Du *et al.* [32] formulated a two-stage robust model and solved it using developed Bender's dual cutting plane and column-and-constraint generation for a reliable p-CLP. The general formula for p-CLP is

$$Z_{p-center} = \min L \quad (9)$$

Subject to

$$\sum_{j \in J} y_{ij} = 1, \ \ i \in I \quad (10)$$

$$\sum_{j \in J} x_j = p \quad (11)$$

$$\sum_{j \in J} d_{ij} y_{ij} \leq L \quad (12)$$

$$y_{ij} \leq x_j \quad (13)$$

$$y_{ij} \in \{0,1\} \quad (14)$$

$$x_j \in \{0,1\} \quad (15)$$

$$L \geq 0 \quad (16)$$

Some notations that are used in the p-CLP modeling:

$Z_{p-center}$ = Objective function of p-CLP model

$y_{ij} = \begin{cases} 1, \text{if the request point } i \text{ is established at prospective location } j\text{;} \\ 0, \text{otherwise.} \end{cases}$

The objective function (9) minimizes the range or traveled period of the maximum weighted request between the request point and the closest facility allocation. Constraint (10) states that only one facility can cover each request point. Constraint (11) shows the number of facilities built. Then, Constraint (12) determines the distance or time of the maximum weighted request. Constraint (13) indicates that open facilities cover the request point. Constraints (14) - (15) are binary integer constraints, and Constraints (16) are non-negative constraints.

B. MBP

MBP locates facilities in prospective areas to find the minimum weighted average fees of the range. We measured the distance from the request point to the assigned facility and located the facility at the midpoints of the network. These issues can be categorized as the location-allocation problem. Irawan *et al.* [33] expanded an ILP model to determine the optimum capacity of the open facility's location. They used compromise programming and VNS to execute the model. Then, Mokhtar *et al.* [34] combined the two-allocation p-hub median problem and a modified Benders Decomposition algorithm for solving hub location problems. They solved the hub median problem by designing a hub network in which the location of p-hubs needs to be decided. Finally, Romero *et al.* [35] used the Tabu search approach for solving the p-median problem. MBP is divided into p-MLP and FCFLP.

1) p-MLP

p-MLP is the most well-known type of FLP that establishes p facilities in a network. The model formulation of the p-MLP is

$$Z_{p-median} = \min \sum_{i \in I} \sum_{j \in J} w_i d_{ij} y_{ij} \quad (17)$$

Subject to

$$\sum_{j \in J} y_{ij} = 1 \quad (18)$$

$$\sum_{j \in J} x_j = p \quad (19)$$

$$y_{ij} \leq x_j \quad (20)$$

$$y_{ij} \in \{0,1\} \quad (21)$$

$$x_j \in \{0,1\} \quad (22)$$

The objective function (17) of the p-MLP minimizes the weighted request's entire range or traveled period. In addition, Constraint (18) shows that only one facility serves each request point. Constraint (19) states the number of facilities built. Constraint (20) shows that assignments are only given to open facilities. Constraints (21)-(22) are binary integer constraints.

2) FCFLP

FCFLP is almost similar to p-median problems. Model p-median problem ignores the difference in the building facilities cost at various candidate locations. In contrast, FCFLP strives to get the minimum total fees from opening and traveling the facility. The general model of the FCFLP is

$$Z_{FCLP} = \min \sum_{j \in J} f_j x_j + v \sum_{i \in I} \sum_{j \in J} w_i d_{ij} y_{ij} \quad (23)$$

Subject to

$$\sum_{j \in J} y_{ij} = 1 \quad (24)$$

$$y_{ij} \leq x_j \quad (25)$$

$$y_{ij} \in \{0,1\} \quad (26)$$

$$x_j \in \{0,1\} \quad (27)$$

The notation v shows the transportation fees variable in one distance unit. The objective function (23) minimizes the opening facilities and transportation fees. Constraint (24) ensures that open facilities serve each demand point, while Constraint (25) restricts assignments only to open facilities. Constraints (26)-(27) show binary integer solutions.

In capacitated FCFLP, we defined a new parameter U_j as the maximal capacity at each facility j. The Capacitated FCFLP is the same as the FCFLP model with a capacity Constraint (28).

$$\sum_{i\in I} w_i y_{ij} \leq U_j, \qquad j \in J \tag{28}$$

C. Different Problems

Different problems are other problems that are not included in covering-based and median-based. Maximum dispersion, p-dispersion, and MNS location problems are included in this category. The maximum dispersion problem exaggerates the mean split distance between open facilities. We located p facilities in the p-dispersion problem and maximized the minimum range between opened facilities. It can be implemented in service facilities, service systems, or retails.

Lai *et al.* [36] developed two evolutionary algorithms to fix the generalized max-mean dispersion problem. They reported computational results on 160 benchmark instances. Sandoval *et al*. [37] solved the p-center-based dispersion minimization problem by improving an exact algorithm. It assigns the base number of health staff employed in an area.

This section also discusses some heuristic algorithms to solve discrete location problems, such as genetic algorithm, particle swamp optimization, and greedy reduction algorithm. The brief explanations are as follows:

A. Genetic Algorithm (GA)

The first stage in the GA is to evaluate the fitness value of each individual based on the given objective function. The crossover process is a gene exchange between two individuals to produce new individuals. The next stage is a mutation, which changes the value of genes in an individual. The GA process determines the new generation according to the objective function. Chromosomes in each individual are composed of several value genes. Genes can be integer, float, binary, character, or combinatorial values. Values contained in one gene are called alleles. The population starts by initializing some individuals. Each individual is a collection of genes called chromosomes. The GA is arranged with columns and rows to form a binary number matrix.

Matrix rows are chromosomes, while the column number is the gene number. The gene number is the multiplication of the Nvar value (the number of variables) with the Nbit value (the number of bits). In contrast, the row number in a matrix is UkPop (population size) [39].

The fitness value measures whether or not a solution is expressed as an individual on an existing problem. The fitness value can be used to achieve the optimal solution [40]. The GA aims to find individuals with the highest fitness value (for the maximization case) or the lowest (for the minimization case). The better the fitness value of an individual, the more likely that individual will survive and continue to the next generation. The fitness value of each chromosome can be calculated as follows:

$$\sum_{j=1}^{n} s_{ij} c_{ij} \tag{29}$$

s_{ij} = binary value of the j^{th}column in the i^{th} chromosome
c_j = distance value of the j^{th}column

Selection is used to select individuals in the interbreeding and mutation. The first step in the selection is finding the fitness value, which will be used in the following stages. The higher the fitness value of an individual (maximum case), the more likely it is to be selected, or the smaller the fitness value of an individual (minimum case), the more likely it is to be chosen. In this study, the selection method used is roulette wheel selection, where the individual or parent is selected based on their fitness value. The steps for the roulette wheel selection process are as follows:

a. Calculate the relative fitness value (p_i) with

$$p_i = \frac{\text{fitness value } (i)}{\text{total of fitness value}} \tag{30}$$

b. Calculate the cumulative fitness value (q_i) with

$$q_i = q_{(i-1)} + p_i \tag{31}$$

c. Generate random numbers in [0,1] as much as the population size in the problem. Then select the i^{th} chromosome as the surviving chromosome using the rule:

$$q_{(i-1)} \leq r_i \leq p_i \tag{32}$$

The better the quality of a chromosome, the greater the chance of being selected as parents in the following process, namely crossover. Crossover aims to find new values, combining two or more chromosomes to become a new chromosome. We exchange genetic information on the parent chromosome to replace some traits or characteristics on the resulting new chromosome [41].

In this study, the method used for the crossbreeding process is the one-point crossover method. This method uses the crossover probability (PC). This study uses 0.25, then generates a random number (r) at [0, 1] and compares it with the PC value. If the r on the chromosome is less than the PC value, then the chromosome will be crossed. Then, to select the position to be crossed, the crossing process is done by generating random numbers from 1 to n (chromosome length).

Mutations aim to get a new chromosome with the best fitness value by replacing several selected parent or parent chromosome genes. Mutation probability is used to determine the rate of mutation that occurs. A high mutation rate will cause the offspring to be more similar to the parent. A good mutation probability is 0.01 – 0.3 [42]. The first step is to count the number of genes by multiplying the population size by the chromosome length. The mutation probability (PM) in this study uses 0.01, then generates at [0,1] as many as the gene number. Genes with a random number value (r) smaller than the predetermined PM value will undergo a mutation process.

B. Particle Swamp Optimization (PSO)

According to [43], the steps in running the PSO algorithm are as follows:

1. Initialize the position (X) and speed (v)
2. Determine the open facility using Eq (33)

$$Y_i = \lfloor |X_i mod\ 2| \rfloor \quad (33)$$

3. Evaluate the fitness value
4. Determine personal best and global best
5. Update the velocity (v) and position (X) using Equation (34) and (35)
$$v_i^{(t+1)} = w.v_i^{(t)} + c_1 r_1 \left(p_i^{(t)} - X_i^{(t)}\right) + c_2 r_2 \left(g^{(t)} - X_i^{(t)}\right) \quad (34)$$
$$X_i^{(t+1)} = X_i^{(t)} + v_i^{(t+1)} \quad (35)$$
6. Update the open facility using Eq (33)
7. Evaluate the fitness value
8. Determine the new personal best and global best
9. Take the global best position (X_g) vector as s_0
10. Update s_0 with Eq (36) based on η and k and give a new name, namely s.
$$g_i = \begin{cases} g_i + 1, \text{jika } g_i \geq 0 \text{ atau } g_i < -1 \\ g_i + 2, \text{jika} -1 \leq\ g_i < 0 \end{cases} \quad (36)$$
11. Apply the flip operator on s and get s_1.
12. Compare the fitness value s_1 with s.
If $f(s_1) \leq f(s)$ then change s to s_1.
If the condition is not met then repeat the steps until the maximum iterations as n many times.
13. Compare the fitness value s_0 with s.
If $f(s) \leq f(s_0)$, then change s_0 to s.
14. If the iteration has been maximum or has converged, then stop the algorithm process, if it is not maximized then repeats step 4.

C. Greedy Reduction Algorithm (GRA)

GRA is an algorithm that is commonly used to solve optimization problems. One of the optimization problems is determining the optimal facility point in a place. Several constraining factors include the distance between the best final solution in the form of a globally optimum solution. There are several essential elements in the facility and the location quality. GRA is an algorithm used to solve optimization problems sequentially, producing a local optimum at each step and producing the function, feasibility, and objective function. The steps of GRA are as follows:

1. Form a distance matrix D with size $m \times n$.
2. Look for the dominating matrix value in all existing matrix columns, provided that the dominating column is the one with a smaller value than the other column values $d_{ik} \leq d_{il}\ ; \forall i \neq k$ and $\forall i \neq l$.
3. From the selected dominating column select the dominating value by comparing all columns with the dominant column.
4. Finding the optimum value by comparing the entry values between columns with the selected dominant column.
5. From the selected dominant column pair, the column is then compared again with each column and looks for the optimum value of the comparison.
6. Analyze the results of each step and recapitulate the results.

IV. Numerical Experiments

The case study used for the numerical experiment is the Temporary Disposal Places (TDP) data in Kertapati District, Palembang City. This section will determine the optimal TDP using the SCLP model, p-Median Problem, and GRA. TDP data in Kertapati District was obtained from the Environmental and Hygiene Office of Palembang City, which was then surveyed and grouped based on the TDP location in each village. Table II shows the distribution of TDP based on village location points.

TABLE II
TDP Based on Village Location Points

No	Village	TDP
1	Ogan Baru	Kemang Gajah Mungkur Kemang Pintu Besi Kertapati Kemang Kertapati Market Kemang Simpang Kencong
2	Kertapati	Sunan Market Kemang PJKA Station
3	Kemas Rido	Infront of Kader Bangsa Mataram
4	Kemang Agung	Jepang Dekat Rumah Ketua DPR Abi Kusno Infront of Zikon 12 Ki Marogan
5	Keramasan	-
6	Karya Jaya	-

Based on Table II, Ogan Baru Village has four TDP, Kertapati Village has two TDP, Kemas Rido Village has only one TDP, and Kemang Agung Village has three TDP. Keramasan Village and Karya Jaya Village do not have any TDP. The definitions of variables for TDP and villages in the Kertapati District are stated in Table III and Table IV.

TABLE IIII
The Variables of TDP in Kertapati District

Variable	List of TDP Names
p_1	TDP Kemang PJKA Station
p_2	TDP Kemang Kertapati Market
p_3	TDP Kemang Pintu Besi Kertapati
p_4	TDP Kemang Simpang Kencong
p_5	TDP Kemang Gajah Mungkur
p_6	TDP Sunan Market
p_7	TDP Abi Kusno Infront of Zikon 12
p_8	TDP Infront of Kader Bangsa Mataram
p_9	TDP Ki Marogan
p_{10}	TDP Jepang Near Ketua DPR House

TABLE IV
The Variables of Villages in Kertapati District

Variable	List of Villages
q_1	Ogan Baru
q_2	Kertapati
q_3	Kemas Rido
q_4	Kemang Agung
q_5	Keramasan
q_6	Karya Jaya

Based on Table III and Table IV, there are 10 TDP and 6 Villages in Kertapati District. Parametre p_1 defines TDP Kemang PJKA Station, p_2 defines TDP Kemang Kertapati Market, and so on. For the village, q_1 defines Ogan Baru Village, q_2 defines Kertapati village, and so on. The distance between each TDP can be seen in Table V. The distance with grey highlights in Table V mean that the allowable distance is 500 m.

TABLE V
THE DISTANCE BETWEEN EACH TDP

$d_{i,j}$	1	2	3	4	5	6	7	8	9	10
1	0	380	440	610	710	1410	2040	2180	2880	4080
2	380	0	60	230	330	1030	1660	1800	2500	3700
3	440	60	0	170	270	970	1600	1740	2440	3640
4	610	230	170	0	100	800	1430	1570	2270	3470
5	710	330	270	100	0	700	1330	1470	2170	3370
6	1410	1030	970	800	700	0	630	1500	2200	3400
7	2040	1660	1600	1430	1330	630	0	2330	3030	4230
8	2180	1800	1740	1570	1470	1500	2330	0	700	1900
9	2880	2500	2440	2270	2170	2200	3030	700	0	1200
10	4080	3700	3640	3470	3370	3400	4230	1900	1200	0

We can see that the distance between TDP 1 and TDP 2 is 380 m, the distance between TDP 1 and TDP 3 is 440 m, and so on. Using the data in Table III-Table V, the SCLP model is presented in Eq (37)-(46).

Minimize:

$$Z_{SCLP} = p_1 + p_2 + p_3 + p_4 + p_5 + p_6 + p_7 + p_8 + p_9 + p_{10} \quad (37)$$

Subject to

$$p_1 + p_2 + p_3 \geq 1 \quad (38)$$
$$p_1 + p_2 + p_3 + p_4 + p_5 \geq 1 \quad (39)$$
$$p_2 + p_3 + p_4 + p_5 \geq 1 \quad (40)$$
$$p_6 \geq 1 \quad (41)$$
$$p_7 \geq 1 \quad (42)$$
$$p_8 \geq 1 \quad (43)$$
$$p_9 \geq 1 \quad (44)$$
$$p_{10} \geq 1 \quad (45)$$
$$p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10} \in \{0,1\} \quad (46)$$

The objective function (37) minimizes the number of TDP to satisfy all demand points. Constraint (38) to Constraint (45) state at least 1 request must be met for each TDP. Constraint (46) states that the variables p_1 to p_{10} are binary. The optimal solution of the model is attached in Table VI.

There are six optimal solutions of SCLP model, and then we measured the distance between each villages and the optimal TDP, that can be seen in Table VII.

TABLE VI
OPTIMAL SOLUTIONS OF SCLP MODEL

Variable	List of TDP Name
p_3	TDP Kemang Pintu Besi Kertapati
p_6	TDP Sunan Market
p_7	TDP Abi Kusno Infront of Zikon 12
p_8	TDP Infront of Kader Bangsa Mataram
p_9	TDP Ki Marogan
p_{10}	TDP Jepang Near Ketua DPR House

By using the data in Table VI and Table VII, the formulation of p-Median Problem Model is presented in Eq (47)-(62).

TABLE VII
DISTANCE BETWEEN VILLAGES AND TDP

$d_{i,j}$	3	6	7	8	9	10
1	1800	1400	2150	2400	3400	4600
2	400	650	1550	1800	2300	3500
3	2600	2200	2950	1100	1700	2900
4	1500	900	450	1000	1900	3100
5	3000	2250	1550	2800	3100	1900
6	8600	8150	8250	6800	5900	5500

Minimize

$$Z_{P-Median} = 1800q_{1,3} + 1400q_{1,6} + 2150q_{1,7} + 2400q_{1,8} + 3400q_{1,9} + 4600q_{1,10} + 400q_{2,3} + 650q_{2,6} + 1550q_{2,7} + 1800q_{2,8} + 2300q_{2,9} + 3500q_{2,10} + 2600q_{3,3} + 2200q_{3,6} + 2950q_{3,7} + 1100q_{3,8} + 1700q_{3,9} + 2900q_{3,10} + 1500q_{4,3} + 900q_{4,6} + 450q_{4,7} + 1000q_{4,8} + 1900q_{4,9} + 3100q_{4,10} + 3000q_{5,3} + 2250q_{5,6} + 1550q_{5,7} + 2800q_{5,8} + 3100q_{5,9} + 1900q_{5,10} + 8600q_{6,3} + 8150q_{6,6} + 8250q_{6,7} + 6800q_{6,8} + 5900q_{6,9} + 5500q_{6,10} \quad (47)$$

Subject to

$$q_{1,3} + q_{1,6} + q_{1,7} + q_{1,8} + q_{1,9} + q_{1,10} = 1 \quad (48)$$
$$q_{2,3} + q_{2,6} + q_{2,7} + q_{2,8} + q_{2,9} + q_{2,10} = 1 \quad (49)$$
$$q_{3,3} + q_{3,6} + q_{3,7} + q_{3,8} + q_{3,9} + q_{3,10} = 1 \quad (50)$$
$$q_{4,3} + q_{4,6} + q_{4,7} + q_{4,8} + q_{4,9} + q_{4,10} = 1 \quad (51)$$
$$q_{5,3} + q_{5,6} + q_{5,7} + q_{5,8} + q_{5,9} + q_{5,10} = 1 \quad (52)$$
$$q_{6,3} + q_{6,6} + q_{6,7} + q_{6,8} + q_{6,9} + q_{6,10} = 1 \quad (53)$$
$$p_3 + p_6 + p_7 + p_8 + p_9 + p_{10} = 6 \quad (54)$$
$$q_{1,3}, q_{2,3}, q_{3,3}, q_{4,3}, q_{5,3}, q_{6,3} \leq p_3 \quad (55)$$
$$q_{1,6}, q_{2,6}, q_{3,6}, q_{4,6}, q_{5,6}, q_{6,6} \leq p_6 \quad (56)$$
$$q_{1,7}, q_{2,7}, q_{3,7}, q_{4,7}, q_{5,7}, q_{6,7} \leq p_7 \quad (57)$$
$$q_{1,8}, q_{2,8}, q_{3,8}, q_{4,8}, q_{5,8}, q_{6,8} \leq p_8 \quad (58)$$
$$q_{1,9}, q_{2,9}, q_{3,9}, q_{4,9}, q_{5,9}, q_{6,9} \leq p_9 \quad (59)$$
$$q_{1,10}, q_{2,10}, q_{3,10}, q_{4,10}, q_{5,10}, q_{6,10} \leq p_{10} \quad (60)$$
$$q_{1,3}, q_{2,3}, q_{3,3}, q_{4,3}, q_{5,3}, q_{6,3}, q_{1,6}, q_{2,6}, q_{3,6}, q_{4,6}, q_{5,6}, q_{6,6}, q_{1,7}, q_{2,7}, q_{3,7}, q_{4,7}, q_{5,7}, q_{6,7}, q_{1,8}, q_{2,8}, q_{3,8}, q_{4,8}, q_{5,8}, q_{6,8}, q_{1,9}, q_{2,9}, q_{3,9}, q_{4,9}, q_{5,9}, q_{6,9}, q_{1,10}, q_{2,10}, q_{3,10}, q_{4,10}, q_{5,10}, q_{6,10} \in \{0,1\} \quad (61)$$
$$p_3, p_6, p_7, p_8, p_9, p_{10} \in \{0,1\} \quad (62)$$

In the next stage, the TDP point solutions obtained from the p-Median model are solved by GRA with the following steps.

Step 1:

Determining the distance matrix D between villages and TDP in Kertapati District

$$D = \begin{bmatrix} 1800 & 1400 & 2150 & 2400 & 3400 & 4600 \\ 400 & 650 & 1550 & 1800 & 2300 & 3500 \\ 2600 & 2200 & 2950 & 1100 & 1700 & 2900 \\ 1500 & 900 & 450 & 1000 & 1900 & 3100 \\ 3000 & 2250 & 1550 & 2800 & 3100 & 1900 \\ 8600 & 8150 & 8250 & 6800 & 5900 & 5500 \end{bmatrix}$$

Step 2:

Get the dominating column by comparing each entry in the matrix column. We compare each column to the other columns.

Step 3:

Compare each column entry with the dominant result, find the smallest dominant value, and add up the smallest dominant value. Tables VIII and IX show the final calculation results from comparing each column with others.

TABLE VIII
COMPARISON RESULTS OF EACH COLUMN WITH COLUMN 2

Column	1	3	4	5	6
2	15300	14400	13100	12800	12550

TABLE IX
COMPARISON RESULTS OF EACH COLUMN WITH COLUMN 3

Column	1	2	4	5	6
3	15050	14400	13600	13300	14100

From Table VIII and IX, the minimum value of the comparison between column 2 and the other columns is in column 6, 12,550. At the same time, the minimum value of the comparison between column 3 and the other columns in column 5 is 13,300. So, the selected columns are columns (2, 6) and (3, 5). We use these two selected columns to compare them with the other columns.

Step 4:

Compare the selected dominant column pair with each column and find the optimum value of the comparison, which can be seen in Table X-XI. We compare columns (2, 6) to columns 1, 3, 4, and 5 and columns (3, 5) to columns 1, 2, 4, and 6.

TABLE X
COMPARISON RESULTS OF EACH COLUMN WITH COLUMN 2 AND 6

Column	1	3	4	5
(2,6)	12300	11750	11450	12050

TABLE XI
COMPARISON RESULTS OF EACH COLUMN WITH COLUMN 3 AND 5

Column	1	2	4	6
(3,5)	11.800	11.650	12.700	12.900

Based on Table X, the minimum value is in column 4, so columns 2, 6, and 4 are the first pair of the optimal solutions. At the same time, from Table XI, the minimum value is in column 2, so columns 3, 5, and 2 are the second pair of optimal solutions.

Step 5:

Analyze the results of each step. Based on steps 1 to step 4, it is found that the completion of the first pair of columns for the first village is 2, 6, 4, and the second pair of columns for the second village is 3, 5, 2 with the following explanation:

1. Solution 2 is the second column matrix, TDP Kemang Pintu Besi.
2. Solution 6 is the sixth column matrix, TDP Jepang Near Ketua DPR House.
3. Solution 4 is the fourth column matrix, TDP Infront of Kader Bangsa Mataram.
4. Solution 3 is the third column matrix, TDP Abi Kusno infront of Zikon 12.
5. Solution 5 is the fifth column matrix, TDP Ki Marogan.
6. Solution 2 is the second column matrix, TDP Kemang Pintu Besi.

We also solve the p-Median model by using LINGO 13.0. that can be seen in Table XII.

TABLE XII
OPTIMAL SOLUTIONS OF P-MEDIAN PROBLEM MODEL

No	Village	Facility Location (TDP)	
		LINGO	GRA
1	Ogan Baru	TDP Sunan Market	TDP Sunan Market
2	Kertapati	TDP Kemang Pintu Besi	TDP Jepang Near Ketua DPR House
3	Kemas Rido	TDP Infront of Kader Bangsa Mataram	TDP Infront of Kader Bangsa Mataram
4	Kemang Agung	TDP Abi Kusno Infront of Zikon 12	TDP Abi Kusno Infront of Zikon 12
5	Keramasan	TDP Abi Kusno Infront of Zikon 12	TDP Ki Marogan
6	Karya Jaya	TDP Jepang Near Ketua DPR House	TDP Sunan Market

Based on Table XII, there are some different solutions between LINGO and GRA especially in Kemas Rido village, Keramasan village, and Karya Jaya village. By analyzing the solution, we figure out the optimal TDP in Figure 1.

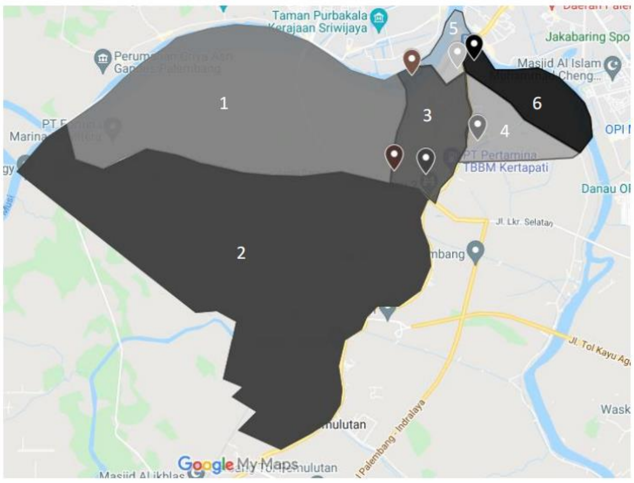

Fig 1. Optimal TDP in Kertapati District

Map description:

1	Keramasan Village		TDP Kemang Pintu Besi
2	Karya Jaya Village		TDP Abi Kusno Infront of Zikon 12
3	Kemang Agung Village		TDP Sunan Market
4	Kemas Rido Village		TDP Infront of Kader Bangsa Mataram
5	Ogan Baru Village		TDP Ki Marogan
6	Kertapati Village		TDP Jepang Near Ketua DPR House

From Figure 1, it can be seen TDP Sunan Market will be placed in Ogan Baru village, TDP Kemang Pintu Besi will be places in Kertapati village, TDP Infront of Kader Bangsa Mataram will be placed in Kemas Rido village, and TDP Abi Kusno Infront of Zikon 12 will be placed in Kemang Agung village. Keramasan Village did not initially have a TDP, so TDP Ki Marogan will be placed in this village based on the solution. In the beginning, Karya Jaya Village did not have a TDP solution either. The LINGO software shows that TDP Jepang near Ketua DPR house should be placed in Karya Jaya Village, while GRA places TDP Sunan Market in Karya Jaya Village. The solutions of the two applications are far different from the actual distance. Adding some new TDP in Karya Jaya Village is suggested for this study.

V. CONCLUSION

This paper briefly introduced the general model formulation for every problem in discrete location problems. We reviewed the fundamental models, surveyed some proposed methods and types of models, and summarized the study in discrete location problems. We implemented the GRA to solve the SCP model and find the optimal TDP in Kertapati District. We believe that this research will be helpful for readers and researchers who are interested in the facility location problem. Hopefully, this paper will encourage researchers and practitioners of operation research to develop the study. More reviews of the facility location problems with heuristics and metaheuristic methods are critically important to develop and apply in some applications for further analysis.

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