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Capacitated Location Allocation Problem of Solar Power Generation in Indonesia using Particle Swarm Optimization

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ABSTRACT

Indonesia has abundant potential for solar energy. The decrease in the cost of solar power generation components can bolster the development of solar power plants. Due to its geographical characteristics, it is essential to analyze the feasibility of using solar power plants as a primary renewable energy source in Indonesia, especially on Sumatra Island. One of the critical aspects of developing solar power plants is determining the suitable location of the power plant and allocating the electricity generated to the regions. Therefore, this study considers the Capacitated Location Allocation Problem (CLAP) to determine the optimal placement of solar power plants on Sumatra Island to minimize investment and transmission costs. To address the problem, we explore three metaheuristics, namely Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Large Neighborhood Search (LNS). The results obtained by these metaheuristic methods show significant differences in cost, with SA providing the best solution with the lowest cost. The investment and transmission cost can be minimized by solving the CLAP to obtain optimal solar power plant placement while enhancing the region's resilience in implementing distributed generation.

1. Introduction

Electricity is one of the most essential forms of energy needed by Indonesia. The demand for electricity is expected to continue increasing over time. Indonesia still relies on non-renewable energy sources for electricity, such as coal and petroleum. One of the issues arising from the use of non-renewable energy sources is their limited quantity. The extensive use of non-renewable energy sources and exceptionally high carbon gas emissions also have negative impacts. According to data from Climate Watch in 2020, the energy sector contributed 73.2% of greenhouse gas emissions. The consequence of these

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greenhouse gas emissions is an increase in temperature, commonly called global warming. Given the limited quantity of non-renewable energy resources and the growing demand for electricity in Indonesia, there is a need for new renewable energy resources that are environmentally friendly, easily accessible, and abundant for public use. According to the Ministry of Energy and Mineral Resources, Indonesia has significant potential for new renewable energy resources (EBT), including mini/micro hydro at 450 MW, biomass at 50 GW, solar energy at 4.80 kWh/m2/day, wind energy at 3-6 m/s, and nuclear energy at 3 GW [1]. Furthermore, solar energy is the most feasible for mass distribution compared to other renewable energy sources because it can be harnessed in almost all regions of Indonesia. Solar energy distribution in Indonesia's western region is approximately 4.5 kWh/m2/day with a monthly variation of 10%. In contrast, in the eastern region of Indonesia, it is around 5.1 kWh/m2/day with a monthly variation of 9% [2]. Based on this data, it is evident that Indonesia receives abundant sunlight throughout the year, with better solar radiation potential in the eastern part compared to the western part [3]. In theory, Indonesia can develop both small-scale and large-scale solar power plants with its abundant solar energy potential and the decreasing costs of solar power generation components.

Considering the varying energy demands across different regions and the capacity limitations of these facilities, the efficient placement of solar power facilities is paramount. Addressing this issue is crucial for maximizing energy output and minimizing costs, optimizing land use, and reducing environmental impact. The Capacitated Location Allocation Problem (CLAP) is a pivotal concern. This complex issue revolves around determining optimal locations for facilities, considering both capacity constraints and demand requirements, to achieve the most efficient allocation of resources. Moreover, the characteristics of solar power plants allow for the implementation of distributed generation. Unlike traditional centralized power generation, distributed generation refers to a method in which some electrical energy is produced and delivered to customers using small units near end-users. Distributed generation encompasses various locally installed power generation units, which can be renewable or conventional. Currently, due to technological advancements, significant benefits can be obtained from distributed generators (DG) in the economic, technical, and environmental aspects [4].

Distributed generation is a promising future for electricity generation in power networks, as it also can harness alternative energy sources. The contributions of distributed generation to the power system include increased energy efficiency and power quality for reliability and security. These benefits can only be achieved by optimally allocating distributed resources, considering objectives constraints, and using appropriate optimization algorithms [5]. In the optimization of distributed generation, the algorithms used can be divided into two main classes: classical algorithms and metaheuristics algorithms. Classical algorithms include mathematics-based methods and basic search approaches. One study using classical algorithms is by Rider, et al. [6], which discusses a bilevel approach to determine the optimal location and contract price for distributed power generation in radial distribution systems. The researchers used mixed-integer linear programming with constraints such as the capacity of distributed generation units, voltage and channel capacity constraints, investment costs, and energy prices. The results showed that the bilevel approach provides better solutions than the single-level approach. It also helps increase the participation of distributed power generators and promotes the use of renewable energy in distribution systems.

Another study employing classical methods is by Gautam and Mithulananthan [7]. They presented two new methodologies for the optimal placement of distributed power generation in optimal power flow based on the wholesale electricity market. The DG is assumed to participate in the wholesale electricity market in real time. The optimal placement problem, including its size, was formulated for two objectives: maximizing social welfare and maximizing profits. Candidate locations for DG placement were identified based on the locational marginal price (LMP), and consumer payments are evaluated as the product of LMP and the load at each load bus. The proposed methodologies were tested on a modified IEEE 14-bus test system with various DG cost characteristics. The obtained results demonstrated that the proposed methodologies can optimize the placement and size of DG in the wholesale electricity market to achieve the set objectives. A study by Hung, et al. [8] discussed the optimal placement of distributed generation units in an electrical distribution network using a metaheuristics algorithm. The authors considered controllable and non-controllable DG units and aimed to minimize energy losses in the distribution network. They employed a genetic optimization algorithm to solve the placement optimization problem, considering various constraints such as DG unit capacity, voltage constraints, and channel capacity. Simulation results indicated that placing dispatchable DG units near heavy loads and non-dispatchable DG units in areas with high potential for renewable energy yields the best outcomes.

Gomez-Gonzalez, et al. [9] also utilized a metaheuristics algorithm, specifically Particle Swarm Optimization (PSO), to improve the performance of distributed power generation systems. They applied discrete PSO to find optimal values for DG system control parameters such as capacity, location, and power factor, optimizing system performance under various operational scenarios. They used the Optimal Power Flow (OPF) to ensure the system's operating conditions met technical and economic constraints. The results showed that the proposed method optimizes the performance of the DG system by minimizing production costs and reducing power losses in the electrical grid. Moreover, this method exhibited excellent capability in finding optimal solutions with shorter computational times than other optimization methods. Gandomkar, et al. [10] discussed using a genetic algorithm and tabu search to determine the optimal location and size of DG units in distribution networks. The method aimed to optimize system performance and reduce operating costs. The research findings demonstrated that the proposed algorithm provides better solutions than previously used methods, such as ordinary genetic or tabu search algorithms alone. The proposed method can also be applied to more complex distribution systems with more DG units.

Mohammadi and Nasab [11] used PSO to determine the placement of DG in radial distribution systems to reduce actual power losses and enhance system reliability. They used a hybrid objective function for optimal DG placement, consisting of two parts. The first part considered the objective of reducing power losses using the Power Loss Reduction Index. The second part considered the impact of DG units on system reliability using the Reliability Improvement Index. The proposed method was tested on a standard IEEE 12-bus test system and is compared to other approaches from the literature. The results showed that the proposed method outperforms other methods regarding solution quality and computational efficiency. Sedighizadeh, et al. [12] identified the optimum location for DG units by introducing power loss and voltage profiles as variables in the objective function. They have utilized PSO and Clonal Selection Algorithm (CLONALG) in previous research to optimize various objective functions. This paper combined PSO and Clonal Selection Algorithm (PCLONALG) as a problem-solving tool to obtain superior solutions. The research results demonstrated that PCLONALG outperforms PSO and CLONALG regarding solution quality and the number of iterations. This combined approach has advantages over both previous methods.

The literature review reveals significant work on the CLAP for solar power plant placement. However, none of these studies specifically focus on Indonesia, a country with

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a high potential for solar energy. This oversight underscores the necessity of a targeted study on solar power plant placement within Indonesia, particularly on Sumatra Island. This research intends to fill this gap by concentrating on CLAP to determine optimal locations for solar power plants and efficiently allocating the electricity they generate across Sumatra, leveraging Indonesia's rich solar resources to enhance energy sustainability and distribution efficiency. Like many other regions, Sumatra faces an increasing electricity demand. Being renewable and abundant, solar energy offers a sustainable solution to meet the region's energy needs. However, Sumatra is home to unique and diverse ecosystems and is prone to natural disasters such as earthquakes. By strategically placing solar power plants, the impact on local ecosystems can be minimized, enhancing the region's resilience.

Three metaheuristic methods are proposed in this study to solve the problem, namely SA (Simulated Annealing), LNS (Large Neighborhood Search), and PSO (Particle Swarm Optimization). The SA has been employed in reentrant permutation flow-shop scheduling [13], facility layout planning [14], [15], parallel partial disassembly line balancing problem [16], allocation of regional water resources [17], and home health care supply chain [18]. The LNS has been used in distributed reentrant permutation flow shop scheduling [19], [20], flying sidekick traveling salesman problem with multiple drops [21], sequence-dependent job sequencing and tool switching problem [22], production routing problem [23], vehicle routing problem with multiple routes [24], static multi-vehicle bike-repositioning problem [25], vehicle routing problem with time windows [26], vehicle routing problem with delivery options [27], and vehicle routing problem with cross-docking [28]. Meanwhile, the PSO has been utilized in mixed-variable optimization problems [29], multimodal multi-objective optimization [30], Safety-enhanced UAV path planning [31], and variable optimization in cervical cancer data [32]. Inspired by the effectiveness of metaheuristics in previous studies, this study addresses CLAP for determining solar power generation in Indonesia using metaheuristic methods with those algorithms. In summary, the contributions of this study are two-fold: (i) This study develops optimization methods for determining the solar power plant placement in Indonesia, especially in the Sumatra region, and (ii) this study explores three metaheuristics -SA, LNS, and PSO – which are specifically developed to solve the CLAP.

2. Methods

2.1 Problem Formulation

The problem formulation used in the capacitated location-allocation problem for determining solar power generation in Sumatra Island is presented as Equation (1)-(5).

Objective function:

$$Min \sum_{i=1}^{I} y_i f_i + \sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij} C_{ij} d_j \tag{1}$$

Subject to:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij} d_j \leq S_i \tag{2}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij} d_j = D_j \tag{3}$$

$$y_i < X_{ij} \tag{4}$$

$$y_i, X_{ij} \in [0,1] \tag{5}$$

Where:

y_i	Binary variable, 1 if a plant is located in province i, 0 otherwise
f_i	capital expenditure cost for establishing a plant in province i
X_{ij}	Binary variable,1 if province j is supplied from province i, 0 otherwise
C_{ij}	transfer cost from province i to province j
D_j	total demand in province j
d_j	allocation demand in province j
S_i	Total supply that province i can provide

The objective function of the CLAP for solar power plants is minimizing the total costs, which consist of the cost of making solar power plants and transmission costs, as shown in Eq. (1). Constraint (2) limits that total electricity transmitted from a solar power plant to all regions must not exceed its capacity. Meanwhile Constraint (3) states that the total electricity transmitted from any solar power plant to a region must be the same as the region's demand. Eqs. (4-5) are the constraints for the decision variable.

Further, several assumptions are held in this study, such as (i) this study only considers the capital expenditure cost for establishing plants. Meanwhile, the investment for electricity network infrastructure is omitted, (ii) the distance to calculate electricity transmission cost from province i to province j is calculated as the distance between the respective provincial capital, and (iii) it is assumed that no energy is lost in the process of transmitting electricity from one region to another.

2.2 Proposed Metaheuristics

2.2.1 Simulated Annealing

The SA algorithm was first introduced in 1959 by Metropolis et al.. It was adapted from the annealing process used to create crystals from a material. The annealing process involves cooling a solid object until its structure freezes at a minimum energy state [33]. The material is heated to a certain point during the crystal formation process, allowing atoms to move freely with high energy. Then, the temperature is gradually lowered, aiming to reduce the energy to a relatively low level. The slower the cooling rate, the lower the energy the system reaches. Thus, the atoms are expected to be in an optimal position with minimum energy.

The simulated annealing algorithm can be seen as a local search that sometimes produces solutions with higher cost (worse) than expected and may reach a local optimum [33]. The disadvantage of SA, which often leads to local optima at certain times, distinguishes it from other local search algorithms. Acceptance of a new solution is based

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on a certain probability of finding the global minimum of a function with multiple local minima.

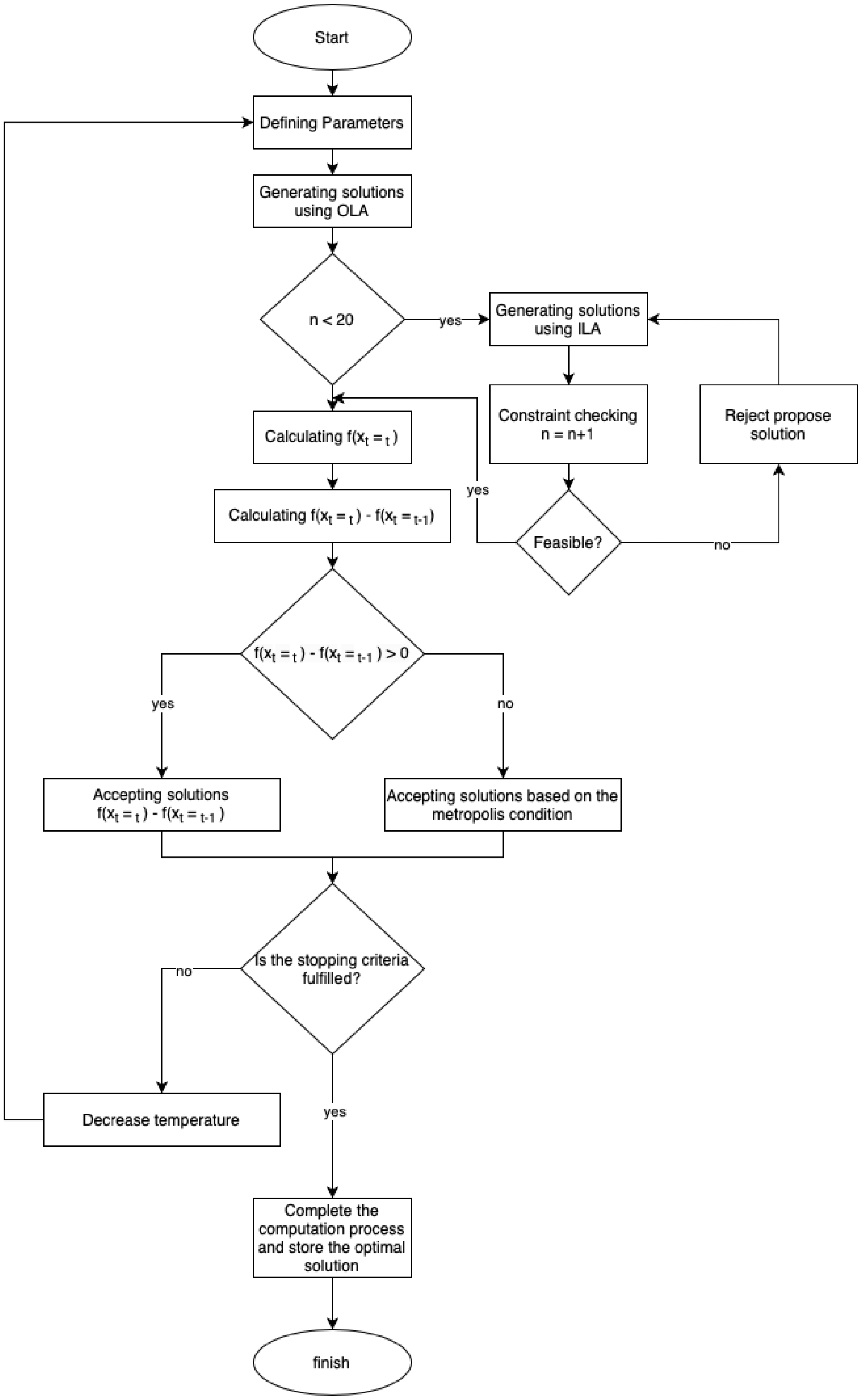

Figure 1. Flowchart of SA algorithm

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Three components to consider in the simulated annealing algorithm, according to [34] are as follows:

1. Annealing Process

The annealing process is the primary process of SA, aiming to prevent the SA system from being trapped in a local minimum. This process depends on the following parameters:

a) Initial temperature: The initial temperature is chosen as high as possible to broaden the acceptance of new solutions.
b) Number of iterations at each temperature: Temperature reduction is performed after reaching a certain number of iterations L. The number of iterations at each temperature can be constant or variable.
c) Selection of parameters for temperature reduction: Temperature reduction is performed using a parameter α called the cooling rate, which ranges between 0 and 1. The temperature reduction process can be expressed as follows: $H_t = \alpha H_{t-1}$, where H_t is the temperature at time t, and H_{t-1} is the temperature at time t - 1.

2. Restructuring

Restructuring or forming a new neighborhood solution is done randomly by modifying the existing solution. This procedure can vary depending on the problem type.

3. Termination of the Algorithm

In terminating the algorithm, a predetermined criterion is required from the beginning. This criterion can be a minimum temperature, where the process stops when the temperature reaches the minimum value. Another criterion is a specific number of iterations, where the process stops if no new solution is accepted after the iteration limit is reached.

Figure 1 presents the logical flowchart of SA. The general steps of the simulated annealing algorithm are as follows:

1. Determine the initial solution α.
2. Determine the initial temperature H_0, final temperature H_f, cooling rate α, and number of iterations L.
3. Set the initial temperature H_0 as the control for accepting or rejecting new solutions.
4. Form the neighborhood solution σ'. The neighborhood solution σ' is formed by randomly rearranging the previously determined initial solution.
5. Calculate the objective function difference (Δσ) using Eq. (6):

$$\Delta\sigma = e(\sigma') - e(\sigma) \tag{6}$$

Where e(σ') is the objective function value of the neighborhood solution σ', and e(σ) is the objective function value of the current solution σ. If Δσ < 0, the neighborhood solution is accepted as the new solution. If Δσ > 0, there are two possibilities: a) The neighborhood solution is accepted: The neighborhood solution is accepted if a randomly generated number P between 0 and 1 is smaller than exp(-Δσ/H), where H is the current temperature or the initial temperature that controls whether the new solution will be accepted or not. b) The neighborhood solution is not accepted: If the randomly generated number P between 0 and 1 is not smaller than exp(-Δσ/H), the current solution remains unchanged, meaning the neighborhood solution is not accepted as the new solution.

6. Check if the number of iterations has reached L. If the number of iterations has not reached L, perform a suitable neighborhood solution restructuring by repeating steps 4 and 5 until the specified iteration limit is reached. If L is reached, proceed to step 7.

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7. Check if the temperature has reached the minimum temperature. If the temperature has not reached the minimum temperature, reduce the temperature H using a cooling rate parameter α, and repeat steps 4, 5, and 6 until reaching the minimum temperature. If the minimum temperature is reached, proceed to step 8.
8. The simulated annealing algorithm process is completed, and the final solution is obtained.

2.2.2 Large Neighborhood Search

The LNS method is a technique in combinatorial optimization aimed at improving the efficiency and effectiveness of search algorithms by expanding the search range or possible solutions. The LNS method involves solving a problem by removing a number of variables or parts from the initial solution, searching for new solutions in the vicinity of that area, and expanding the solution by reintroducing the removed variables or parts.

The LNS algorithm was first introduced by Shaw [35]. It is an algorithm that searches for solutions using local search methods. Local search is a method for finding solutions based on the neighborhood of an initial solution. Figure 2 presents the logical flowchart of LNS. The large neighborhood search algorithm has three main stages in solving the VRP problem.

1. Initial Solution Formation The initial solution can be generated randomly or using heuristic algorithms.
2. Neighborhood Solution Formation The formation of neighborhood solutions is done using deletion and improvement methods [36]. The deletion method disrupts or modifies existing solutions. In contrast, the improvement method rebuilds the solutions modified by the deletion method. The neighborhood solution N(σ') of σ is a set of solutions obtained through deletion and improvement methods.
3. Evaluation Function Value Calculation The evaluation function value is calculated by comparing the initial solution with the evaluated neighborhood solution based on the objective function until the best solution is reached.

The general steps of the large neighborhood search algorithm are as follows:

1. Determine the initial solution σ.
2. Determine the number of iterations ɭ to be used.
3. Initialize the initial solution (σ) as the global best solution (σ'').
4. Form the neighborhood solution using deletion and improvement methods to obtain the neighborhood solution (σ').
5. Calculate the objective function value of the initial solution f(σ'') and the neighborhood solution (σ').
6. Determine whether the neighborhood solution (σ') will be accepted as a new solution to replace the current solution. If f(σ') < f(σ''), then update the solution, meaning the neighborhood solution (σ') is accepted as the new solution. If f(σ') > f(σ''), then the neighborhood solution (σ') is not accepted as a new solution and proceed to step 7.
7. Check if the iteration has reached the ɭ limit. If the iteration has not reached ɭ, perform a suitable reformation of the neighborhood solution by repeating steps 4, 5, and 6 until reaching the ɭ iteration. If it has reached the iteration, proceed to step 8.
8. The Large Neighborhood Search algorithm process is completed, and the best solution (σ'') is obtained as the final solution.

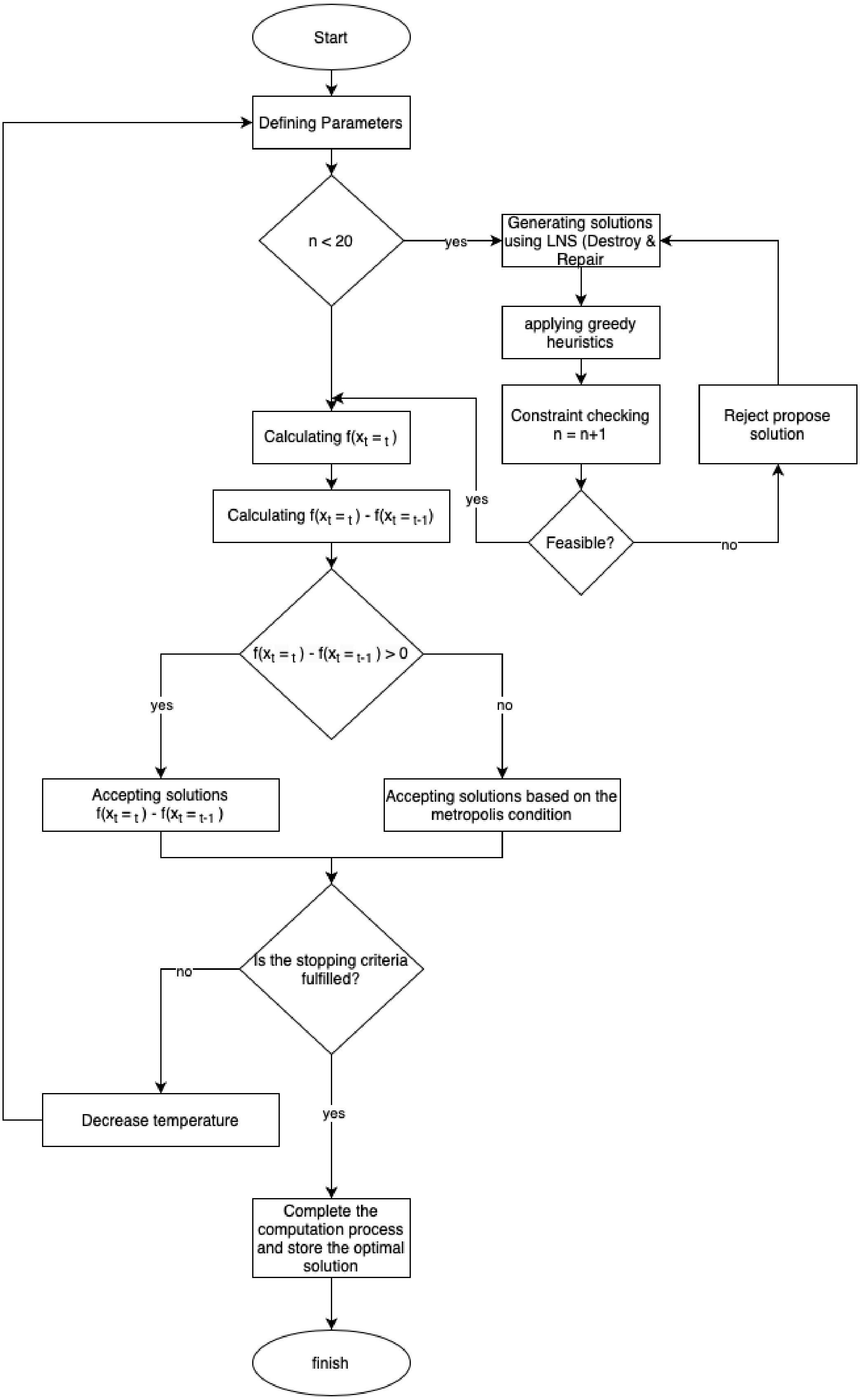

Figure 2. Flowchart of LNS algorithm

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2.2.3 Particle Swarm Optimization

PSO is a global optimization method introduced by Kennedy and Eberhart in 1995 based on the study of the flocking behavior of birds and fish. Each particle in PSO has a particle velocity that dynamically adjusts based on its historical behavior in the search space. Therefore, particles tend to move towards better search areas during the search process [37].

In PSO, the search is influenced by two types of learning by particles. Each particle learns from other particles and has its own experience while moving. Learning from others is social learning while learning from one's own experience is cognitive learning. As a result of social learning, particles store in their memory the best solutions visited by any particle in the swarm, known as gbest. As a result of cognitive learning, particles store in their memory the best solution they visited so far, known as pbest. The direction and magnitude of particle movement are determined by velocity [38]. Figure 3 presents the logical flowchart of PSO.

The PSO algorithm has several components and parameters described as follows:
1. Swarm Size: The number of particles in the swarm.
2. Inertia Weight (ω): Controls the impact of the previous velocity on the new velocity.
3. Acceleration Coefficients (c1 and c2): Control the influence of personal and global best positions on the particles' movement.
4. Search Space: The range of values particles can search for solutions.
5. Termination Criteria: Conditions under which the algorithm stops iterating.

The PSO algorithm consists of several processes described as follows:
1. Initialization:
    - Initialize a swarm of particles randomly in the search space.
    - Assign random velocities to particles.
    - Define fitness function to evaluate the solutions.
2. Evaluation:
    - Evaluate the fitness of each particle in the swarm using the defined fitness function.
    - Update each particle's personal best positions (pbest) based on their fitness.
    - Update the global best position (gbest) by selecting the particle with the best fitness among all particles.
3. Updating Velocities and Positions:
   Update the velocity of each particle using the following formula:
   new_velocity = ω × old_velocity + c1 × rand() × (pbest − current_position) + c2 × rand() × (gbest − current_position)
   Here, ω is the inertia weight, c1 and c2 are acceleration coefficients, and rand()rand() generates a random number between 0 and 1.
   Update the position of each particle using its new velocity:
   new_position = current_position + new_velocity
4. Update Personal and Global Best:
   Update personal best positions (pbest) if the fitness of the current position is better than the previous personal best.
   Update the global best position (gbest) if any particle finds a better solution than the current global best.
5. Termination Criteria:
   Check if termination criteria are met. It can be a maximum number of iterations, a target fitness value, or a time limit.

6. Iteration:
   Repeat steps 2 to 5 until the termination criteria are met.
7. Output:
   Return the best solution found or the particle's position corresponding to the global best fitness value.

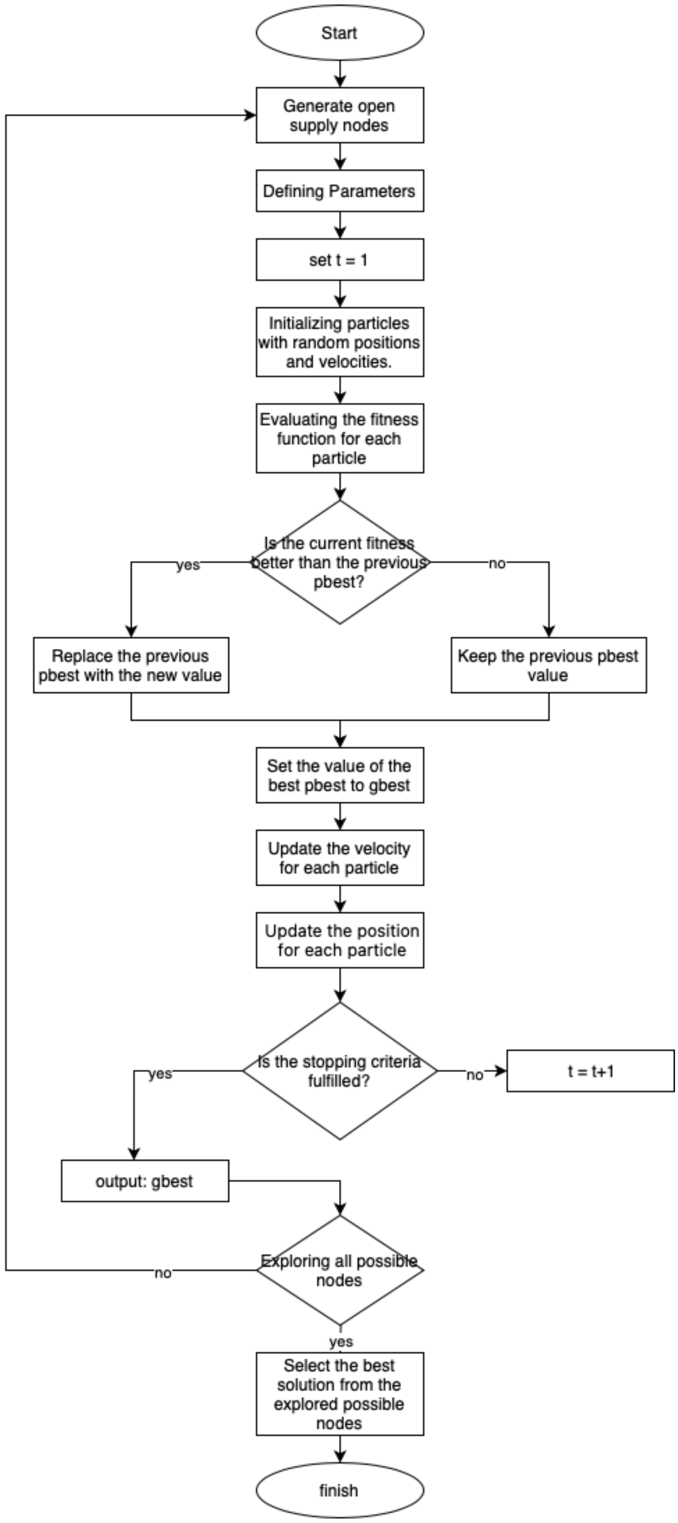

Figure 3. Flowchart of PSO algorithm

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2.3 Dataset

The following are each province's energy demand data and distance measurement data (Table 1).

Table 1. Total population per province

Province	Total Population Projected by Province and Gender (in Thousand People)					
	2015	**2016**	**2017**	**2018**	**2019**	**2020**
Aceh	5,018.7	5,094.5	5,169.4	5,243.4	5,316.3	5,388.1
Sumatera Utara	13,961.4	14,136.8	14,308.4	14,476	14,639.4	14,798.4
Sumatera Barat	5,200.9	5,272.5	5,342.8	5,411.8	5,479.5	5,545.7
Riau	6,356.7	6,478.4	6,598.7	6,717.6	6,835.1	6,951.2
Jambi	3,403.9	3,445.9	3,487	3,527.1	3,566.2	3,604.2
Sumatera Selatan	8,062.7	8,174.1	8,283.8	8,391.5	8,497.2	8,600.8
Bengkulu	1,875.9	1,900.7	1,924.9	1,948.6	1,971.8	1,994.3
Lampung	8,123	8,210.3	8,295.3	8,377.7	8,457.6	8,534.8
Indonesia	255,587.9	258,496.5	261,355.5	264,161.6	266,911.9	269,603.4

Table 2. Distance Measurement (in km)

Distance (Km)	Banda Aceh	Medan	Pekanbaru	Jambi	Palembang	Bandar Lampung	Bengkulu	Padang
Banda Aceh	0	602	1,194	1,630	1,897	2,266	1,881	1,236
Medan	602	0	644	1,074	1,343	1,741	1,342	702
Pekanbaru	1,194	644	0	457	725	1075	757	311
Jambi	1,630	1,074	457	0	274	641	446	579
Palembang	1,897	1,343	725	274	0	383	443	782
Bandar Lampung	2,266	1,741	1,075	641	383	0	568	1094
Bengkulu	1,881	1,342	757	446	443	568	0	540
Padang	1,236	702	311	579	782	1094	540	0

The data in Table 2 regarding the distances between the two provinces is further processed to obtain the cost required to transmit electricity from one region to another. The transfer cost is assumed to be based on the distance unit, with a cost of 4.4 USD per MW per 1000 miles, while the cost required to build a solar power plant is 550 USD/MWh. The results of converting the distances into costs are shown in Table 3.

Table 3. Result from converting distance to cost

From/To	Aceh	Sumatera Utara	Riau	Jambi	Sumatera Selatan	Lampung	Bengkulu	Sumatera Barat
Aceh	0.00	1.65	3.27	4.46	5.19	6.20	5.14	3.38
Sumatera Utara	1.65	0.00	1.76	2.94	3.67	4.76	3.67	1.92
Riau	3.27	1.76	0.00	1.25	1.98	2.94	2.07	0.85
Jambi	4.46	2.94	1.25	0.00	0.75	1.75	1.22	1.58
Sumatera Selatan	5.19	3.67	1.98	0.75	0.00	1.05	1.21	2.14
Lampung	6.20	4.76	2.94	1.75	1.05	0.00	1.55	2.99
Bengkulu	5.14	3.67	2.07	1.22	1.21	1.55	0.00	1.48
Sumatera Barat	3.38	1.92	0.85	1.58	2.14	2.99	1.48	0.00

Meanwhile, the projected supply and demand for each province for 2025 is depicted in Table 4. The supply data represents the potential capacity of solar energy in a province. In contrast, the demand data is obtained by extrapolating the electricity demand using

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the exponential smoothing method based on historical electricity demand data in each province from 2015 to 2020.

Table 4. Projected Demand and Potential Capacity per provinces in 2025

Province	Projected Demand (MWh)	Potential Capacity (MWh)
Aceh	2,884,348.4	6,316,722
Sumatera Utara	10,335,262.6	22,634,225
Riau	4,856,586.2	10,635,923
Jambi	1,983,332.9	4,343,499
Sumatera Selatan	5,283,538.9	11,570,950
Lampung	4,870,410.5	10,666,198
Bengkulu	994,248.3	2,177,403
Sumatera Barat	3,425,297.8	7,501,402

3. Results and Discussion

The experiments are executed using Python with the following computer specifications: operating system of Windows 10 Education 64-bit (10.0, Build 19045), Intel(R) Core(TM) i5-10400F CPU @ 2.90GHz (12 CPUs), ~2.9GHz processor, 16384 MB RAM, NVIDIA GeForce GTX 1660 SUPER graphic card.

3.1 Results of Simulated Annealing

Based on the results obtained from the SA method, the cost required to meet the electricity demand using solar power plants is US$ 57 billion. According to the solution provided by the Simulated Annealing method, three provinces will build power generation facilities to meet the electricity demand in Sumatra Island, namely Aceh, Jambi, and West Sumatra. Aceh province will supply electricity to its province and North Sumatra by utilizing the potential capacity of 23.5%. Jambi province will supply electricity to its province, South Sumatra, Lampung, and Bengkulu, utilizing a potential capacity of 49%. West Sumatra province will supply electricity to its province and Riau province, utilizing the potential capacity of 25.1%. Table 5 presents the energy distribution results of the best solution obtained by SA.

Table 5. Energy distribution of the best solution from the Simulated Annealing (in MWh)

From/To	Aceh	Sumatera Utara	Riau	Jambi	Sumatera Selatan	Lampung	Bengkulu	Sumatera Barat
Aceh	865,304.4	3,100,578. 8	0.00	0.00	0.00	0.00	0.00	0.00
Jambi	0.00	0.00	0.00	1,456,975.8	594,999.9	1,585,061.7	29,8274.5	0.00
Sumatera Barat	0.00	0.00	1,027,589.3	0.00	0.00	0.00	0.00	1,461,123.1
Total Demand	865,304.4	3,100,578.8	1,027,589.3	1,456,975.8	594,999.9	1,585,061.7	29,8274.5	1,461,123.1

3.2 Results of Large Neighborhood Search

Based on the results obtained from the LNS method, the cost required to meet the electricity demand using solar power plants is US$75 billion. According to the solution provided by the Large Neighborhood Search method, four provinces will build power plant facilities to meet the electricity demand in Sumatra Island: Aceh, Jambi, Bengkulu, and Padang. Aceh province will supply 99.9% of the electricity needed by the provinces on Sumatra Island. Meanwhile, Jambi, Bengkulu, and Lampung will each contribute only 1

MWh. Table 6 presents the energy distribution results of the best solution obtained by LNS.

Table 6. Energy distribution of the best solution obtained by LNS

From/To	Aceh	Sumatera Utara	Riau	Jambi	Sumatera Selatan	Lampung	Bengkulu	Sumatera Barat
Aceh	865,304	3,100,578	1,027,589	1,456,975	594,999	1,585,061	298,274	1,461,123
Jambi	0	0	0	1	0	0	0	0
Lampung	0	0	0	0	0	1	0	0
Bengkulu	0	0	0	0	0	0	1	0

3.3 Results of Particle Swarm Optimization

Based on the results obtained from the PSO method, the cost required to meet the electricity demand using solar power plants is $78 billion. According to the solution provided by the particle swarm optimization method, one province, namely Aceh, will build power plants to meet the electricity demand on Sumatra Island. Aceh province will supply 100% of the electricity needed by all provinces in Sumatra Island. Table 7 presents the energy distribution results of the best solution obtained by LNS.

Table 7. Energy distribution of the best solution obtained by PSO

From/To	Aceh	Sumatera Utara	Riau	Jambi	Sumatera Selatan	Lampung	Bengkulu	Sumatera Barat
Aceh	865,304.4	3,100,578.8	1,027,589.3	1,456,975.8	594,999.9	1,585,061.7	29,8274.5	1,461,123.1

3.4 Discussion

The results indicate that SA performs slightly better than the LNS method built in this paper, as evidenced by the average cost function values generated by both methods in 200 iterations. The SA is built using the layering approach proposed by Qin and Miao [39], where the outer layer is the facility search process built on the solution space Y_i, while the inner layer is the decision-making process for province j service by facility i on the solution space X_{ij}. Thus, the search process for a solution X_{ij} depends on the results Y_i provided by the outer layer algorithm. Therefore, the solution search process is performed across the entire solution space in the SA, even though the SA algorithm does not have specific systematics in the allocation process to minimize overall costs.

The Large Neighborhood Search has an advantage in searching for local optima with greedy heuristics applied in this algorithm, allowing for a more systematic search process. However, the LNS algorithm used is limited to the solution space X_{ij}, and the value of Y_i is determined as a consequence of the resulting solution X_{ij}. In other words, this paper's large neighborhood search algorithm cannot explore the entire solution space, making it difficult to search for near-optimal solutions.

The results of this study differ from the findings of Gomez-Gonzalez, et al. [9] and Mohammadi and Nasab [11], in which the PSO fell behind other methods with higher total costs. Theoretically, PSO has the advantage of being able to find reasonable global solutions because particles can collaboratively explore the entire search space. However, the results of PSO are susceptible to the configuration of the parameters used, so choosing inappropriate parameters can affect the results obtained and the speed of the solution search. In this problem, PSO gets trapped in local optimal, where each replication's cost value remains unchanged.

This study emphasizes the significance of optimizing solar power plant placement and allocation in Sumatra, Indonesia, through the metaheuristics approach of the Capacitated Location Allocation Problem methodology. This research carries profound implications across several domains. In technological innovation and adoption, this study showcases the application of advanced optimization techniques in real-world energy problems, paving the way for further technological advancements and the adoption of smart energy solutions in the region.

In terms of energy policy and strategy development, the findings of this research can help inform policymakers and stakeholders about the efficiency and potential of solar energy in Indonesia, guiding strategic decisions in renewable energy investments and infrastructure development. By demonstrating cost-effective solutions for solar power deployment, the study encourages financial investments in renewable energy, potentially leading to cost savings in energy production and distribution and stimulating economic growth through job creation in the renewable sector.

4. Conclusion

From the results obtained using the SA, three provinces will build power generation facilities to meet the electricity needs in Sumatra Island, namely Aceh, Jambi, and West Sumatra, with a total cost of US$57 billion. On the other hand, with the LNS, the cost required to meet the electricity needs using solar power plants is US$75 billion. Four provinces will build power generation facilities: Aceh, Jambi, Bengkulu, and Padang. In the PSO, the cost required to meet the electricity needs using solar power plants is US$78 billion, and one province will build a power generation facility, which is Aceh. Based on the results obtained from the metaheuristic methods (SA, LNS, and PSO), there are significant differences in cost. This is due to the specialization of the algorithms in exploiting and exploring solutions. The proposed model and method can assist in determining optimal solar power plant location and the allocation of electricity by minimizing the solar power plant making and transmission costs. For future studies, other factors in the CLAP for solar power plants can be considered, such as by including the factors of environmental impact and demand uncertainty. In addition, the model can be extended into multiple objectives to consider various factors that may have trade-off relationships.

Data Availability

The data supporting this study's findings are available from the corresponding author upon reasonable request.

Declarations

Author contribution: A. W. Astungkatara, H. Fath, O. Putri, A. A. I. A. N. Yana: Data curation, Software, Formal analysis, Investigation Visualization, Writing - original draft; N. M. E. Normasari, A. T. Oktavia, A. P. Rifai: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing

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