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Sustainable Generation and Transmission Expansion Planning Using MOPSO-BPSO in Electrical Grid

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ABSTRACT — As of 2023, approximately 85% of power plants operating in South Sulawesi relied on fossil fuels, such as coal, gas, and oil. To meet the increasing demand for electricity while reducing carbon emissions, it is essential to integrate renewable energy sources into the power system. Renewable energy not only helps conserve fossil fuels but also supports global environmental sustainability. South Sulawesi possesses significant hydro potential, offering opportunities to develop both small and large-scale hydroelectric power plants (*pembangkit listrik tenaga air*, PLTA). This study employed a multi-objective particle swarm optimization (MOPSO) approach to develop optimal scenarios for generation expansion planning (GEP), and binary particle swarm optimization (BPSO) to determine the necessary transmission expansion planning (TEP). The planning process was supported by long-term load forecasting using the moving average method based on historical electricity demand data in South Sulawesi. Results showed that the proposed integrated GEP and TEP optimization framework successfully identified an optimal scenario maximizing renewable energy used while ensuring transmission reliability. By 2030, PLTA is projected to contribute 67.9% of total electricity generation. Meanwhile, steam-fired power plants (*pembangkit listrik tenaga uap*, PLTU) become the mainstay with capacities reaching 437.5 MW. To support this scenario, nine new transmission lines are needed, along with the expansion of 25 existing lines to accommodate increased power flow within the interconnection system.

KEYWORDS — Environmental Sustainability, Generation Expansion Planning, Transmission Expansion Planning, MOPSO, BPSO.

I. INTRODUCTION

The growth in the number of nickel processing industries in Indonesia has triggered an increase in the need for electricity in Sulawesi. In 2023, 85% of the power plants operating in South Sulawesi were power plants that used coal, gas and oil [1]. The rest is generated by hydroelectric power plants (*pembangkit listrik tenaga air,* PLTA) and wind power plants (*pembangkit listrik tenaga bayu*, PLTB). To ensure the availability of electrical energy whose demand is increasing while keeping carbon emissions low, it is necessary to utilize renewable energy resources as electricity generators. In addition to saving fuel, renewable energy-based generators can also reduce carbon emissions. However, the utilization of this energy can only be done in potential areas that are far from adequate load centers. South Sulawesi has a large river flow potential to build PLTA both small and large scale. The capacity that can be obtained by utilizing PLTA reaches 2,368 MW [2]. Through optimal utilization of hydro energy, the dominance of fossil fuel power plants can be reduced so that it will directly reduce carbon emissions.

New power plants require in-depth technical and economic studies. To ensure the economic feasibility, the power generated must be in accordance with the system load requirement. The addition of generators to a system will affect the existing transmission line capacity or network transfer capability (NTC), so that transmission development planning is needed to obtain the minimum investment costs for developing the transmission network while still meeting technical, economic and reliability requirements.

The complexity of generation expansion planning (GEP) has increased over time due to the need to integrate environmental considerations into planning, which adds layers of intricacy to the models used [3]. Numerous studies have been conducted to analyze GEP [3]–[16] Various optimization methods, such as linear programming or mixed-integer programming, are often used to find the most cost-effective mix of generation resources [16]. Practical methodology for GEP incorporating constraints for firm power and reserve requirements to deal with the variability effects of demand and renewable-based generation has been implemented in 2023 [15]. By adding the proposed constraints, the GEP process evolves into a mixed-integer nonlinear programming (MINLP) model. This model is more complex but is expected to yield more flexible and robust solutions for generation expansion planning.

The other study has successfully determined the best investment schedule for new capacity, including the type of technology and the timing for installation. This is crucial for meeting forecasted load while adhering to reliability criteria over a 20-year planning horizon [14]. Mixed integer linear programming (MILP) was carried out using MATLAB software to solve the GEP model. The rate of CO_2 emissions decreased by approximately 30%, whereas the share of renewable energy sources (RES) increased by 35%. This MILP also has succeeded to predict that the installed capacity of renewable energy in Jiangsu Province will rise dramatically from 21.6 GW to 133.2 GW by 2050 in the baseline scenario [13]. This represents an increase in the share of renewable energy from 17.9% to 53.7% of the total capacity. Another research presents a method for least-cost generation expansion planning that effectively incorporates RES using a novel optimization approach. In this study, a hybrid technique combining the correction matrix method (CMM) with the indicators-based discrete water cycle algorithm (IBDWCA) was proposed to address the complexities introduced by the variability and uncertainty of RES. The method optimizes generation mix decisions by minimizing total system costs while ensuring system reliability and sustainability.

A bi-level model consisting of a planning-level model and operational-level model has been conducted in a previous study [12]. The results of the paper underscore the importance of integrating renewable energy and energy storage into power generation planning while also accounting for the impacts of natural disasters on costs and carbon emissions. Another method to account for uncertainties in electricity demand and generation is stochastic optimization [11]. These models help in optimizing the construction and operation of both new and existing power plants. Genetic algorithm (GA) model effectively aids in construction planning for power systems, focusing on reducing the costs associated with installing various types of power plants [10]. It is found that a 10% reduction in the initial investment cost can lead to a significant minimization of overall costs in the proposed model.

Previous studies have tended to separate GEP and transmission expansion planning (TEP), which can lead to mismatches between the location of new power plants and the available transmission infrastructure capacity. In contrast to these studies, this research integrates the multi-objective particle swarm optimization (MOPSO) method for GEP and binary particle swarm optimization (BPSO) for TEP in a unified approach, specifically applied to the South Sulawesi power system, which has significant potential for hydropower development. This approach is expected to produce a more technically and economically optimal long-term expansion plan for the power system. In addition, the application of MOPSO in this context provides advantages in finding optimal solutions that balance investment costs, system reliability, and environmental impacts, which have not been comprehensively explored in previous studies.

II. METHODOLOGY

A. OPTIMIZATION METHOD

Particle swarm optimization (PSO) is an optimization method in which the algorithm imitates the social behavior of flocks of birds or fish. Social behavior consists of individual actions and the influence of other individuals in a group [17]. PSO is an effective tool for solving nonlinear and non-convex optimization problems [18]. Unlike PSO, BPSO is an extension of the PSO method used for optimization problems in binary search space [19]–[20]. The BPSO algorithm has been employed to determine the optimal location and number of new transmission lines required to minimize construction costs and transmission losses [18]. The model ensures voltage limits (±5%) and thermal capacities are not violated. Unlike standard PSO that operates in continuous space, BPSO represents particle positions in the form of values 0 and 1 and uses a transfer function to convert velocities into probabilities of moving between positions. In this study, BPSO method was applied in TEP. Velocity and position update were executed based on (1) and (2).

$$v_{ij}(t) = sig\left(v_{ij}(t)\right) = \frac{1}{1+e^{-v_{ij}(t)}} \quad (1)$$

$$x_{ij}(t+1) = \{1 \quad if\ r_{ij} < sig(v_{ij}(t+1))\ 0 \quad if\ r_{ij} > sig(v_{ij}(t+1)) \quad (2)$$

where v_{ij} is particle velocity, t is iteration, x_{ij} is particle position and r_{ij} is a random number.

Similar to conventional PSO, the personal best and global best of the particle swarm are also updated. In updating the local and global optimum values, there are two vectors that represent the probability of a particle changing. The probability of a particle changing from bit 0 to 1 is denoted by $\vec{V}_i^0$. Conversely, the particle's tendency to change from 1 to 0 is denoted by $\vec{V}_i^1$. Thus, the probability of bit change in a particle is defined by (3) and (4).

$$V_{ij}^c = \{V_{ij}^1\ , if\ x_{ij} = 0\ V_{ij}^0\ , if\ x_{ij} = 1 \quad (3)$$

$$\begin{aligned}
&\text{If } P_{best}^j = 1 \text{ then } d_{ij,2}^1 = c_1 r_1 \text{ and } d_{ij,2}^0 = -c_1 r_1 \\
&\text{If } P_{best}^j = 0 \text{ then } d_{ij,2}^0 = c_1 r_1 \text{ and } d_{ij,2}^1 = -c_1 r_1 \\
&\text{If } G_{best}^j = 1 \text{ then } d_{ij,2}^1 = c_2 r_2 \text{ and } d_{ij,2}^0 = -c_2 r_2 \\
&\text{If } G_{best}^j = 1, \text{ then } d_{ij,2}^0 = c_2 r_2 \text{ and } d_{ij,2}^1 = -c_2 r_2
\end{aligned} \quad (4)$$

where d_{ij}^1 , d_{ij}^0 are two temporary values. The random values r_1 and r_2 , which lie in the interval (0,1), are updated in each iteration.

In addition to utilizing BPSO, this study also applied the MOPSO method to execute two objective functions in GEP analysis. The application of MOPSO in optimizing more than two objective functions has been extensively explored [21]. To adapt the PSO algorithm for multi-objective optimization, the guidance mechanism was adjusted to treat nondominated solutions as leaders. These leaders were particles that steered the rest of the swarm toward more optimal areas within the search space. Several multi-objective PSO models incorporated a mutation operator, often referred to as the turbulence method. After applying this operator, each particle was evaluated, and the corresponding personal best (P_{best}) was updated based on its performance. All evaluated particle positions qualified as nondominated vectors were stored in a repository. This repository was updated by taking into account a geography-based approach, which was defined through the expression of everyone's objective function values using (5).

$$v_{ij}(t+1) = w \times v_{ij}(t) + c_1 r_1\left(p_{ij}(t) - x_{ij}(t)\right) + c_2 r_2\left(R_h(t) - x_{ij}(t)\right) \quad (5)$$

where w is inertial weight with fixed value, c_1 and c_2 are learning rate individual ability (cognitive). R_h are leaders selected from the repository and p_{ij} is the best position updated each iteration.

Compared to single-objective optimization, determining the optimal value in multi-objective optimization is more challenging. In this case, there is no definitive best solution that satisfies all objectives simultaneously. Achieving the optimal result for one objective typically involves making trade-offs with others [21]. A solution that is not outperformed by any other in all objectives is referred to as a nondominated solution. The collection of nondominated solutions from the entire search space is also known as the Pareto set.

Figure 1 shows several points resulting from the evaluation of objective functions f_1 and f_2. When comparing points A and

Jurnal Nasional Teknik Elektro dan Teknologi Informasi
Volume 14 Number 3 August 2025

F, it is evident that F performs better than A in both objective functions, meaning that A is dominated by F. Similarly, when comparing B and F, F yields a better value for objective function f_1 , while both have equal values for f_2. It is indicating that F also dominates B. The outcome of a multi-objective optimization process is a set of solutions that are not just optimal for a single objective but represent trade-offs across multiple objectives.

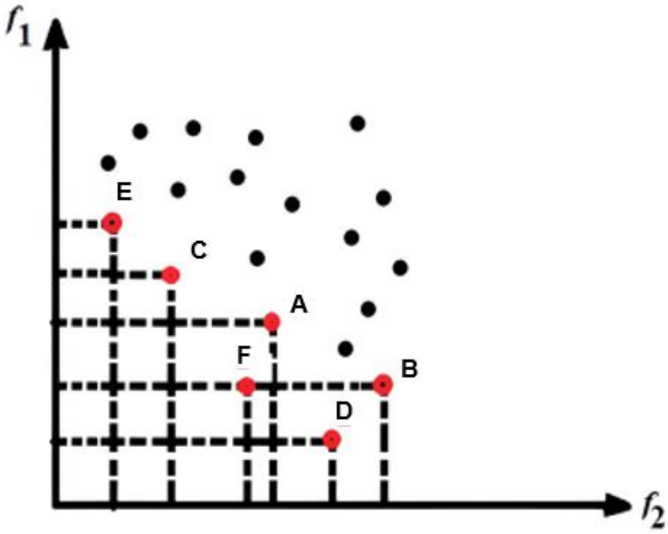

Figure 1. Nondominated solution in MOPSO.

B. OBJECTIVE FUNCTION

Unlike single-objective optimization which focuses on achieving a single best value, multi-objective optimization aims to find a set of optimal solutions that represent a compromise between multiple objectives. The first objective in this study, written as (6), is cost objective function.

$$f_1 = \sum_{(i,j)\in A} C_{ijt}\Delta P_{ijt} + \sum_{t\in T} \frac{1}{1(1+r)^{-t}} \left[\sum_{i\in N} \sum_{q\in \Theta} I_{iqt} U_{iqt} + \sum_{i\in N} \sum_{q\in \Theta} G_{iqt} g_{iq} \right]. \quad (6)$$

Investment costs in this case are the amount of investment costs in the form of the present value of each new generating unit. Investment costs include the initial investment costs and the cost of adding transmission capacity. Variable N is represented as nodes on a transmission line and A is a transmission line. The $i \in N$ node represents the demand or supply point of energy and the direction $(i,j) \in A$ is the transmission line, $q \in \Theta$ is the generating unit. Meanwhile, T is the set of periods in the planning horizon where $t \in T$ is the set of time periods.

Several variables were used in the optimization process of the MGEP model. The g_{iqt} is the power capacity of the generating unit type at node a period t. Y_{iqt} is accumulated capacity (MW) of generating unit type at node if period t. U_{iqt} is the additional power capacity (MW) of generating unit type q at node if period t. P_{ijt} is power flowing on line in period t. ΔP_{ijt} is additional transmission capacity (MW).

In this objective function, r is the discount factor (rate of return) per unit of investment time, I_{iqt} is the investment cost (Rp/MW) of the generating unit type q. $G_{iqt}$is the generating cost (Rp/MW) of the generating unit type q at node i (operation and maintenance) in period t. While $C_{ijt}$is the cost (Rp/MW) for the development of a new transmission line (i, j).

Carbon emissions are the environmental impact of power plant development, especially in fossil fuel power plants. These emissions cannot be absorbed by flora, causing global warming. The second objective function is to minimize carbon emissions from power plants.

$$f_2 = \sum_{t\in T} \left[\sum_{i\in N} \sum_{q\in \Theta} E_q g_{iqt} \right] \quad (7)$$

where $E_q$is the amount of carbon emissions (tons) per MW produced by a generating unit of type q. The two objective functions in (6) and (7) were then evaluated using MOPSO. Unlike the carbon emission objective function, the cost objective function is slightly more complex. It is necessary to select a transmission line to obtain the optimal development cost.

C. CONSTRAINTS

The selection of optimal transmission lines was carried out using the BPSO method. The selection of transmission lines considers cost, power loss, and ensures that the current loading does not exceed 50% of the line's current-carrying capacity. Based on the objective function, several constraints are formulated to obtain the optimization value.

$$\sum_{q\in \Theta} g_{iq} = \sum P_{D_i} + \sum P_{loss_{ij}}. \quad (8)$$

P_{D_i} is the demand/load (MW) on bus i. The optimization carried out considers the amount of power loss $P_{loss_{ij}}$ that occurs in the process of distributing electrical power to the load [22]. Based on the data, the maximum power loss was recorded at 8.1% of the power generated [1]. The maximum power loss occurred during the day. The average power loss was 4.9%.

$$P_{ij(t)} \leq C\Delta P_{ij_0} + \Delta P_{ij_1},\ (i,j) \in A. \quad (9)$$

The amount of power flowing through the line must be smaller than the maximum line load and additional transmission capacity [9]. For various reasons (space, power sources, etc.), there is a maximum amount of power that can be generated.

$$U_{iq} \leq IG_{iq} \quad i \in N,\ q \in \Theta \quad (10)$$

where $IG_{iq}$is the maximum investment (MW) of new generating capacity of type q at node i. A well-prepared power system planning must involve the electricity demand forecasting (EDF) and GEP for better operation [9]. This involves predicting future electricity demand based on historical data, economic indicators, and demographic trends. Accurate load forecasting is essential for determining the capacity needed to meet future energy needs [8].

Another constraint is cumulative power capacity for each generating unit type q at node i during period t. The generated power capacity is accumulated from year to year in planning.

$$Y_{iqt} = Y_{iq(t-1)} + U_{iqt}. \quad (11)$$

The generation capacity during period 0 is equal to GE_{iq}. The existing generating power capacity (MW) for generating unit type q at node i written as in (12).

$$C\Delta x_{ij0} = X_{ij}. \tag{12}$$

The transmission capacity in period 0 is the same as the capacity of the existing transmission channel *(i,j),* namely X_{ij}.

D. RESEARCH DESIGN

This research began with determining the objectives and scope, namely designing a sustainable GEP and TEP using MOPSO approach. Subsequently, data from the existing electrical system were collected, including generation capacities, transmission network structure, load demand profiles, and operational technical constraints. Next, data of potential new generation units and transmission lines were compiled, covering technical characteristics, investment costs, and potential integration of renewable energy sources.

In this study, the calculation of investment costs for power plants and operations was executed by taking into account the interest rate and the rupiah exchange rate. This prediction was conducted using the moving average forecasting method. Moving average is a simple time series forecasting technique that predicts future values by averaging a fixed number of past data points [23]. It is widely used in fields like finance and energy forecasting due to its simplicity and effectiveness. In this case, the prediction process uses historical data on the rupiah exchange rate against the dollar over a period of ten years.

Following this, a mathematical model of the problem was formulated, incorporating multiple objective functions, namely minimizing cost, minimizing carbon emissions, and improving system reliability. This model was subjected to several technical constraints, such as power balance, maximum transmission line capacities, generation output limits, and carbon emission reduction targets.

After the model formulation, the MOPSO algorithm was implemented to find optimal solutions that simultaneously satisfy all objectives. MOPSO parameters were then initialized, and an initial population of particles—each representing a candidate expansion plan—was generated. The initialization mentioned by figure was conducted by generating a population consisting of several particles with the size of the population matrix (n_{pop} , $N_{candidate\times period}$). The value n_{pop} is 50. Before carrying out an objective function evaluation, the population must be ascertained whether it met the criteria $P_{generation} = P_{demand}$.

Next, these particles were evaluated based on the objective functions, and any constraint violations were addressed through penalties or corrective mechanisms. The algorithm then entered an iterative optimization phase, where the nondominated solution archive was updated, leaders were selected to guide particle movement, and velocities and positions were revised accordingly. Each updated solution was reevaluated, and particles' personal bests were updated if improvements were found. Following the evaluation, each solution was checked for constraint satisfaction, ensuring compliance with operational and technical requirements, including power balance, line loading, and generator output limits. If a particle violated constraints, repair mechanisms or penalties were applied. This loop continued until the maximum number of iterations was reached, at which point the algorithm yielded a set of Pareto-optimal solutions. These solutions represent the best trade-offs among multiple planning objectives and serve as decision-making tools for system planners.

MOPSO generates a Pareto front, which is a set of nondominated solutions. However, this set may contain dozens or hundreds of solutions, which can make decision-making difficult. K-means clustering is used to group similar solutions. This method uses a centroid model to perform grouping based on the distance between data points. The commonly used method for calculating distance is the Euclidean distance. The Euclidean distance formula is shown in (13).

$$d(r_k, c_k) = \sqrt{\sum_{k=1}^{n} \ (r_k - c_k)^2} \tag{13}$$

where d is distance, k is number of points, c is centroid, and r is data.

E. ELECTRICAL SYSTEM OF SOUTH SULAWESI

Currently, the power plants in South Sulawesi are interconnected through transmission lines consisting of 275 kV, 150 kV, 70 kV, and 30 kV lines. Figure 2 shows the configuration of the existing and planned transmission network. In the diagram, the red solid and dashed lines represent the existing 150 kV transmission lines, which form the primary backbone of the current power system, interconnecting major generation units and load centers. The blue dashed lines indicate the proposed transmission line expansions, which are planned to enhance system reliability, accommodate future load growth, and support the integration of additional generation capacity, particularly from new power generation. Meanwhile, the yellow solid and dashed lines denote the existing 70 kV transmission lines, which primarily serve as sub-transmission networks for regional load distribution. Last, the green solid line represents the existing 30 kV transmission. The figure also shows generator locations marked with "G," load center and switching substations, highlighting the critical nodes within the network. The marked "G" with a dashed line represents the candidate of the new generator. The combination of existing and planned transmission infrastructure is expected to improve the overall robustness, operational flexibility, and sustainability of the electrical grid in future scenarios.

In this study, a set of potential generation expansion options was considered to support the future needs of a sustainable electrical grid. The candidate power plants vary in type and capacity, representing a diversified mix of thermal, gas, combined cycle, and hydroelectric generation technologies.

The steam-fired power plant (*pembangkit listrik tenaga uap*, PLTU) candidates included G1 (70 MW), G2 (100 MW), G6 (200 MW), G7 (200 MW), and G8 (250 MW). These plants are anticipated to provide substantial base-load capacity to the grid, with a cumulative potential addition of 820 MW from coal-fired generation sources. For medium-speed gas engine power plants (*pembangkit listrik tenaga mesin gas*, PLTMG), three candidates were identified: G3 (50 MW), G4 (100 MW), and G5 (20 MW), providing flexible generation options with a combined capacity of 170 MW. These units are expected to enhance grid reliability due to their relatively fast ramp-up characteristics.

In terms of renewable energy expansion, eleven PLTA were proposed. These include G9 (200 MW), G10 (100 MW), G11 (234 MW), G12 (126 MW), G13 (90 MW), G14 (53 MW), G15 (480 MW), G16 (95 MW), G17 (190 MW), G18 (40 MW), and G19 (35 MW). PLTA are critical in supporting sustainable

Jurnal Nasional Teknik Elektro dan Teknologi Informasi
Volume 14 Number 3 August 2025

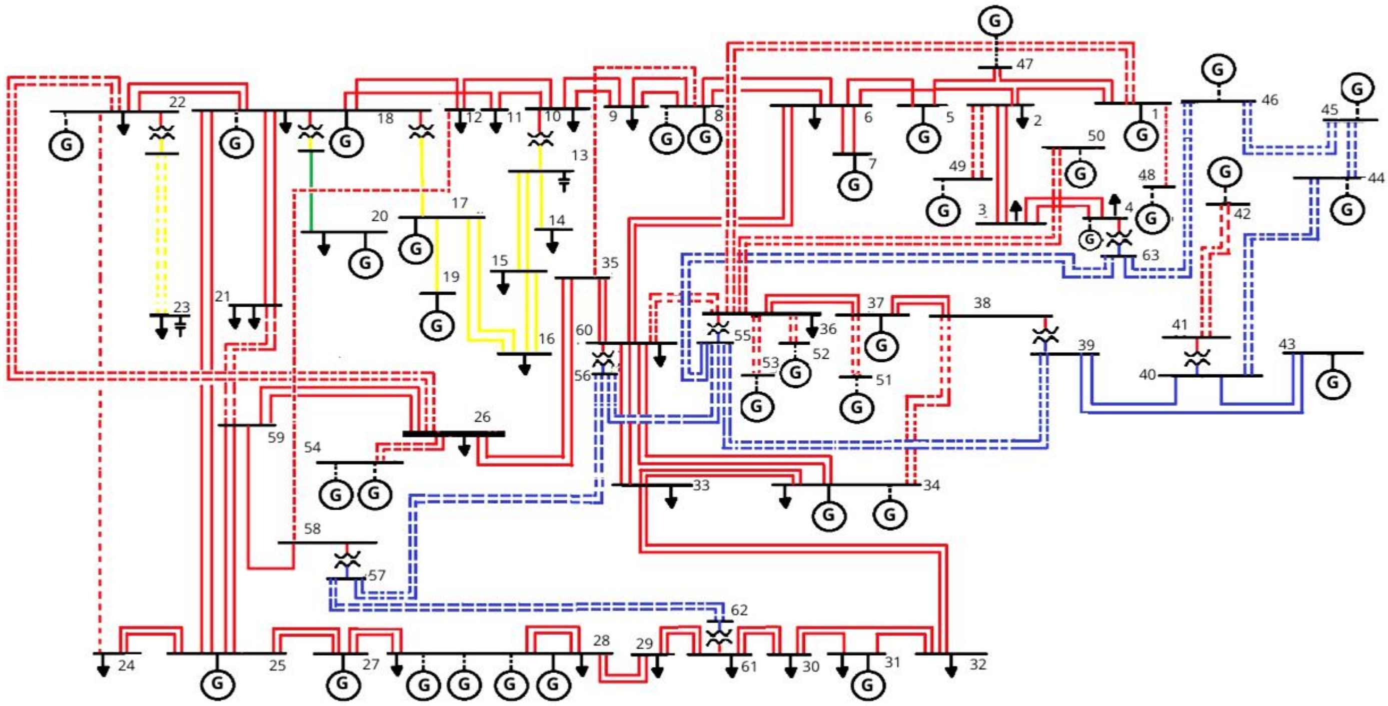

Figure 2. Simplified single line diagram of South Sulawesi electrical grid.

energy goals due to their low carbon emissions. The total potential capacity addition from PLTA is 1,643 MW.

Additionally, two combined-cycle power plants (*pembangkit listrik tenaga gas dan uap*, PLTGU) were considered, namely G20 (450 MW) and G21 (450 MW). These units are expected to provide highly efficient and lower-emission generation compared to conventional thermal plants, offering a total additional capacity of 900 MW. Overall, the potential power plant expansion options offer a wide range of generation technologies and capacities. This diversity is crucial for ensuring system reliability, economic feasibility, and environmental sustainability in the future development of the electrical grid.

To accommodate projected demand growth, facilitate the integration of new generation units, and enhance system reliability, a set of candidate transmission lines were proposed for expansion planning. The candidates included both long-haul and short-distance connections. For instance, T3 represents the longest candidate line, connecting bus 36 to bus 63 over a distance of 420 km, playing a critical role in strengthening the transmission backbone. Similarly, T2 (bus 35 to bus 57, 350 km) and T9 (bus 38 to bus 34, 313 km) provide major long-distance reinforcements crucial for relieving transmission congestion across regions.

On the other hand, shorter lines such as T7 (2 km from bus 8 to bus 60) and T11 (19.2 km from bus 24 to bus 22) were proposed to improve local network resilience and operational flexibility. Mid-range transmission candidates like T4 (160 km from bus 46 to bus 63) and T5 (160 km from bus 38 to bus 36) were intended to enhance interconnection strength between strategic nodes.

III. RESULTS AND DISCUSSION

Figure 3 displays several points representing a collection of nondominated solutions that form the optimal Pareto. The curve that slopes downward from the upper left to the lower right indicates a trade-off between the two objective functions: when the value of f_1 improves (decreases), the value of f_2 tends to worsen (increase), and vice versa. This shows that the two objectives are in conflict, meaning no single solution can optimize both at the same time. With the applied parameters, the solutions obtained were 57. This collection of solutions was then filtered to obtain several alternative power plant planning using the k-means clustering grouping method. The cost function consisted of the accumulation of transmission costs, power plant investment and transmission for power plant development over five periods.

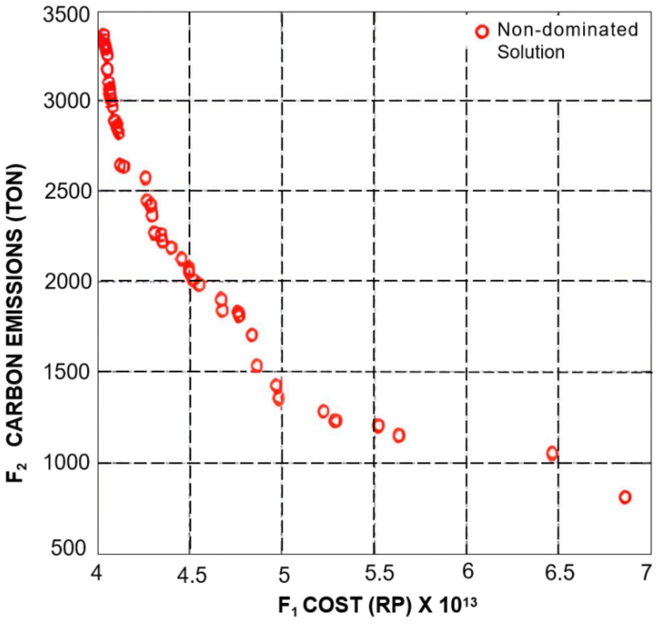

Figure 3. Nondominated solution of two objectives.

TABLE I
ALTERNATIVES FOR ADDING NEW POWER PLANTS, NEW TRANSMISSION LINES, AND EXTENDING EXISTING TRANSMISSION LINES

Alternatives	New Power Plant	New Transmission Line	Extension Transmission Line
S1	G1, G2, G3, G4, G5, G6, G13, G14, G16, G17, 19, G20, G21	T4, T6, T8, T10, T11, T12	L5, L11, L12, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L77
S2	G1, G2, G3, G4, G5, G9, G10, G11, G12, G13, G16, G17, G18, G43, G19, G20, G21	T1, T2, T4, T6, T8, T11, T12	L11, L12, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L46, L47, L50, L77
S3	G1, G2, G3, G4, G5, G6, G10, G13, G14, G16, G17, G19, G20, G21	T4, T6, T8, T9, T10, T11, T12	L5, L9, L11, L12, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L46, L47, L50, L77
S4	G1, G2, G3, G4, G5, G6, G7, G13, G16, G19, G20, G21	T2, T4, T6, T9, T12	L2, L3, L6, L9, L11, L14, L18, L19, L20, L21, L23, L25, L27, L29, L30, L31, L32, L37, L42, L77
S5	G1, G2, G3, G4, G5, G6, G9, G11, G12, G14, G16, G17, G18, G19, G20, G21	T1, T4, T6, T7, T8, T10, T11, T12	L11, L12, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L77
S6	G1, G2, G3, G4, G7, G13, G14, G16, G17, G20, G21	T4, T6, T7, T10, T12	L2, L3, L6, L11, L12, L14, L15, L18, L19, L20, L21, L23, L25, L27, L29, L30, L31, L37, L42, L77
S7	G1, G2, G3, G4, G5, G9, G10, G12, G13, G16, G17, G18, G19, G20, G21	T1, T4, T6, T8, T10, T11, T12	L2, L9, L11, L12, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L46, L47, L50, L77
S8	G1, G2, G3, G4, G5, G6, G7, G8, G9, G10, G11, G12, G13, G14, G16, G17, G18, G19	T4, T8, T10, T11, T12, T13	L3, L10, L11, L12, L14, L15, L18, L19, L20, L21, L25, L26, L27, L30, L31, L32, L38, L46, L47, L50, L54
S9	G1, G2, G3, G4, G5, G6, G7, G9, G10, G12, G13, G14, G15, G16, G17, G18, G19	T3, T4, T5, T6, T7, T8, T9, T10, T12	L3, L5, L9, L10, L11, L12, L13, L14, L15, L18, L19, L20, L21, L27, L30, L31, L32, L38, L46, L47, L50, L54, L59, L63, L75
S10	G1, G2, G3, G4, G5, G7, G10, G13, G14, G17, G18, G20, G21	T1, T4, T6, T8, T10, T11, T12	L2, L9, L14, L15, L18, L19, L20, L21, L26, L27, L29, L30, L37, L77

Based on the optimal Pareto front, the total system cost ranged from a minimum of IDR40,564,074,000,000 to a maximum of IDR68,577,596,000,000, while carbon emissions varied between 812 tons and 3168 tons. This shows that the development of the power plant that requires the most expensive costs produces the least carbon emissions. Conversely, the planning that requires the cheapest costs produces the greatest carbon emissions. The nondominated solution was subsequently refined using k-means clustering, resulting in the selection of ten nondominated solutions that serve as the final alternatives.

The size of the population and the number of iterations employed during the optimization process significantly influenced the number and diversity of nondominated solutions generated. Generally, increasing the population size allows the algorithm to explore a broader solution space, thereby enhancing the probability of identifying a wider range of high-quality, nondominated solutions. Similarly, a greater number of iterations provides the optimization process with more opportunities to refine solutions and approach the true Pareto front more closely.

However, while larger population sizes and more iterations can improve the solution quality and diversity, they also substantially increase the computational burden. This escalation in computational effort not only requires greater processing power and memory resources but also leads to longer optimization times. As such, a careful balance must be struck between achieving sufficient solution quality and maintaining reasonable computational efficiency. In practical applications, this trade-off necessitates a strategic choice of parameters based on the complexity of the problem, available computational resources, and desired optimization performance.

Table I outlines ten alternative scenarios (S1–S10) for sustainable expansion planning in the power system, each consisting of a unique combination of new power plant additions, construction of new transmission lines, and extensions to existing transmission infrastructure.

Across all alternatives, several generator units such as G1 through G5, G13, G16, G17, G19, G20, and G21 appeared frequently, reflecting their strategic importance and suitability in meeting long-term energy demands. PLTA and PLTGU plants were especially prominent, highlighting a consistent focus on renewable and cleaner energy sources. For example, in alternative S9—one of the most comprehensive and sustainability-driven scenarios—the plan included 17 new power plant additions, encompassing a wide variety of generation types, including the prominent inclusion of PLTA and PLTGU units.

Transmission network planning also exhibited a high degree of variation across scenarios. Alternatives such as S2, S3, S7, and S9 proposed an extensive build-out of new transmission lines—up to 9 different candidate lines in some cases—suggesting the necessity to enhance power transfer capabilities across regions. Additionally, the number of transmission line extensions varied significantly among

TABLE II
COMPARATIVE COSTS AND CARBON EMISSIONS FOR EACH ALTERNATIVE

Alternatives	Cost (Trillion Rupiahs)	Carbon Emission (1×10^3 Ton)
S1	4.6803	1.8407
S2	5.6344	1.1561
S3	4.8672	1.5340
S4	4.1491	2.6295
S5	4.9827	1.3587
S6	4.3564	2.2233
S7	5.2964	1.2322
S8	6.4635	1.0586
S9	6.8578	0.8124
S10	4.5555	1.9780

TABLE III
TRANSMISSION, OPERATION, AND INVESTMENT COSTS OF EACH ALTERNATIVE

Alternatives	Cost (Trillion Rupiahs)		
	Transmission	*Operation*	*Investment*
S1	0.0116	0.0009	4.6678
S2	0.0169	0.0008	5.6167
S3	0.0178	0.0009	4.8485
S4	0.0193	0.0010	4.1288
S5	0.0116	0.0008	4.9703
S6	0.0116	0.0009	4.3439
S7	0.0137	0.0008	5.2819
S8	0.0137	0.0006	6.4492
S9	0.0357	0.0005	6.8261
S10	0.0112	0.0009	4.5434

alternatives. S9 proposed the most extensive upgrade with 25 transmission line extensions, indicating a strong push for both capacity reinforcement and network reliability improvement.

While scenarios of S1 and S6 focused on moderate infrastructure changes, others such as S9 and S8 reflected ambitious strategies that aim to accommodate high levels of renewable integration and increase grid flexibility. Each scenario demonstrates a tailored approach, balancing sustainability, cost, and system reliability based on different future planning priorities.

Table II shows the costs and carbon emissions of each alternative power generation planning. The planning with the maximum cost was alternative S9, while the minimum cost was alternative S4. In terms of the carbon emissions of each alternative, S9 was the planning that produced the lowest carbon emissions. The largest carbon emissions were produced by alternative S4. Alternatives S1, S3, and S5 were reasonable trade-offs, potentially near the knee of the pareto front.

Based on Table III, investment costs dominate the total cost across all alternatives. Transmission and operation costs were comparatively negligible. Alternative S4 with 4.1491 trillion was the cheapest alternative. Alternative S9 with 6.8578 trillion was the most expensive. S9 had notably higher transmission costs (0.0357 trillion), nearly three times the others possibly due to more complex grid expansion. S10 had the lowest transmission cost (0.0112 trillion), making it attractive in terms of infrastructure development. S9 and S8 also had the lowest operational costs (0.0005 and 0.0006 trillion), which can be beneficial for long-term operation and maintenance expenses.

Table IV shows biannual grouping of power generation types. PLTA emerged as the dominant option across nearly all

TABLE IV
BIANNUAL GROUPING OF POWER PLANT TYPES

Alternatives	Power Plant	Generated Power (MW)				
		2022	*2024*	*2026*	*2028*	*2030*
S1	PLTA	58	366	105	-	-
	PLTGU	-	-	-	394	437.5
	PLTMG	-	131.5	55	-	-
	PLTU	-	97	193	-	-
S2	PLTA	-	529	223	0	164.5
	PLTGU	-	-	-	394	273
	PLTMG	55	-	131.5	-	-
	PLTU	3	-	66.5	-	-
S3	PLTA	58	336	226	-	-
	PLTGU	-	-	-	394	437.5
	PLTMG	-	132	55	-	-
	PLTU	-	97	72.5	-	-
S4	PLTA	58	204	-	-	-
	PLTGU	-	-	-	394	437.5
	PLTMG	-	186.5	-	-	-
	PLTU	-	205	353.5	-	-
S5	PLTA	-	540.5	163.5	-	-
	PLTGU	-	-	-	394	437.5
	PLTMG	55	-	131.5	-	-
	PLTU	-	-	55	58	-
S6	PLTA	-	410	-	-	-
	PLTGU	-	-	-	394	437.5
	PLTMG	55	92	-	-	-
	PLTU	-	92	353	-	-
S7	PLTA	-	498	222	110	-
	PLTGU	-	-	-	284	437.5
	PLTMG	53	-	131.5	-	-
	PLTU	-	97	-	-	-
S8	PLTA	-	517	278.5	254	-
	PLTGU	-	-	-	-	-
	PLTMG	55	78.5	22	-	-
	PLTU	-	-	53	140	437.5
S9	PLTA	-	574	237	394	44
	PLTGU	-	-	-	-	-
	PLTMG	-	21.5	116.5	-	-
	PLTU	58	-	-	-	394
S10	PLTA	-	410	79	0	0
	PLTGU	-	-	-	394	437.5
	PLTMG	-	185	-	-	-
	PLTU	58	-	274	-	-

scenarios (S1–S10), particularly in the years 2024 and 2026, with the highest generation recorded in scenario S9 in 2024, reaching 574 MW. However, the contribution of PLTA tends to decrease after 2026, even though it is consistently scheduled to begin operation starting in 2028, particularly across nearly all scenarios in which it is included. The generation capacity is stable at 394 MW and increases to 437.5 MW in 2030, indicating the important role of PLTGU in the medium to long term. The utilization of PLTMG varied significantly across scenarios, reaching its highest contribution of 186.5 MW in 2024 under scenario S4. However, its utilization was predominantly concentrated in the early years, specifically between 2022 and 2026.

PLTU will experience an increasing role in 2026 in several scenarios such as S4 and S6, with capacities reaching 353.5 MW and 353 MW respectively. Meanwhile, in alternative S9 and S8, PLTU became the mainstay at the end of the period (2030) with capacities reaching 394 MW and 437.5 MW. Not all power plants were used in every alternative. Some alternatives did not use PLTGU (such as S8 and S9), while other scenarios minimized the use of PLTU to reduce carbon emissions. In 2030, the largest penetration of renewable energy generators will be owned by the S9 alternative. Of the total 1,839 MW, 1,249 MW is generated by PLTA followed by 452 MW of PLTU and 138 MW of PLTMG.

IV. CONCLUSION

The application of MOPSO in Sustainable Generation and Transmission Expansion Planning has proven to be highly effective in addressing the complex, multi-criteria nature of the problem. MOPSO successfully generated a diverse set of non-dominated solutions, allowing for a comprehensive exploration of trade-offs between sustainability, cost, and system reliability. Through the optimization process, MOPSO demonstrated strong capabilities in balancing conflicting objectives, particularly in promoting renewable energy integration while maintaining sufficient power system capacity to meet demand.

PLTA and PLTGU are the main generators that are relied upon sustainably in most alternatives. PLTMG and PLTU are more supportive in the short to medium term, but PLTU still plays an important role in alternative with high power requirements. the period with variations and spikes in contributions from various types of power plants occurred in 2024-2026.

Alternative S9 shows a large focus on renewable, making it a leading candidate from a sustainability perspective. At the end of 2030, PLTA dominates energy contribution with 67.9% of total power. This shows the major dependence on renewable energy sources. However, there is still a reliance on coal-fired power plants, which account for almost a quarter of total power, which is important in the context of reducing carbon emissions.

CONFLICTS OF INTEREST

The author declares that in the implementation and preparation of this research there is no conflict of interest, either financial, personal, or professional, which can affect the objectivity and integrity of the research results. The entire research process is carried out independently without any influence from any party who has an interest in the results of this research. Thus, the results of this research are presented objectively.

AUTHORS' CONTRIBUTIONS

Conceptualization, Astuty and Zainal Sudirman; methodology, Astuty; software, Astuty; validation, Astuty and Zainal Sudirman; formal analysis, Astuty; investigation, Astuty; resources, Astuty; data curation, Astuty; writing—original draft preparation, Astuty; writing—reviewing and editing, Astuty; visualization, Astuty; supervision, Astuty; project administration, Astuty; funding acquisition, Zainal Sudirman.

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Jurnal Nasional Teknik Elektro dan Teknologi Informasi
Volume 14 Number 3 August 2025

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