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Hybrid Particle Swarm Optimization–Simulated Annealing OPF for Lombok Generation Cost Reduction

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ABSTRAK

Penelitian ini mengusulkan penerapan Optimal Power Flow (OPF) pada Sistem Kelistrikan Lombok yang terdiri atas 19 bus dan 7 unit pembangkit, dengan tujuan utama mengurangi biaya produksi pada kondisi beban puncak. Metode yang digunakan merupakan metode optimasi hibrida yang mengombinasikan dua metode yaitu algoritma Particle Swarm Optimization dan Simulated Annealing. Metode Particel Swarm Optimization and Simulated Annealing (PSO–SA). Menggabungkan algoritma PSO dan SA dapat perbaiki kelemahan PSO dengan fitur lompatannya. Dengan kata lain, penggunaan Algoritma PSO-SA lebih efektif dibandingkan metode PSO. Hasil simulasi menunjukkan biaya pembangkitan sebesar USD 31.158. Total daya terbangkit 193,736 MW, yang setara dengan jumlah beban 193,34 MW. Selain itu, profil tegangan seluruh bus berada pada 0,95–1,05 pu dan aliran daya seluruh saluran berada di bawah kapasitas termal. Temuan ini menegaskan bahwa penggunaan Algoritma PSO–SA efektif menekan biaya operasi tanpa melanggar batasan operasi sistem.

***Kata kunci**: Aliran Daya, OPF, PSO-SA, Sistem Kelistrikan Lombok*

ABSTRACT

This study proposes the application of Optimal Power Flow (OPF) in the Lombok Electricity System consisting of 19 buses and 7 generating units, with the main objective of reducing production costs under peak load conditions. The method used is a hybrid optimization method that combines two methods, namely the Particle Swarm Optimization and Simulated Annealing algorithms. Particle Swarm Optimization and Simulated Annealing (PSO–SA) method. Combining PSO and SA algorithms can improve the weaknesses of PSO with its jumping feature. In other words, the use of the PSO-SA algorithm is more effective than the PSO method. The simulation results show a generation cost of USD 31,158. The total generated power is 193,736 MW, which is equivalent to a total load of 193.34 MW. In addition, the voltage profile of all buses is at 0.95–1.05 pu and the power flow of all lines is below the thermal capacity. This finding confirms that the use of the PSO–SA algorithm effectively reduces operating costs without violating the system's operating constraints.

***Keywords**: Lombok Power System, OPF, Power Flow, PSO-SA*

1. INTRODUCTION

Electricity has become an essential requirement for modern life, playing a crucial role in both household consumption and industrial development **(Gopinath & Meher, 2018)**. The rapid growth of demand for electrical energy necessitates the expansion of generation capacity to ensure reliable supply **(Barman et al., 2023)**. At the same time, the integration of renewable resources and economic efficiency in power generation is increasingly important for supporting sustainable industrialization and improving quality of life **(Algarni et al., 2023)**. With ongoing technological advancements and industrial growth, the rising electricity demand highlights the urgency of optimizing generation strategies to maintain cost-effectiveness while meeting load requirements **(Silva et al., 2020)**. Within this context, reducing operating costs remains a primary objective in the efficient management of electrical power systems **(Mubarak et al., 2022)**.

Optimal Power Flow (OPF) is widely regarded as a fundamental optimization challenge in the operation and planning of electrical networks **(Li et al., 2024)**. The central aim of OPF is to minimize generation expenses through the optimal scheduling of active power outputs across multiple generating units **(Yang et al., 2023)**. However, this optimization must be achieved while complying with equality and inequality constraints as well as technical requirements, including bus voltage stability and thermal capacity limits of transmission lines **(Biswas et al., 2020)**. Broadly, OPF solution strategies are divided into deterministic approaches, which rely on mathematical formulations, and non-deterministic or heuristic techniques that employ probabilistic algorithms **(Ebeed et al., 2018)**.

This study focuses on the Lombok interconnected electricity system, which relies on seven fossil fuel-fired power plants: Ampenan Diesel Power Plant, Taman Diesel Power Plant, Sewatama Jeranjang, Jeranjang Steam Power Plant, Paok Motong Diesel Power Plant, Cogindo Pringgabaya, and Sambelia Steam Power Plant. This study investigates power generation optimization across distributed diesel and turbine units with the dual objectives of reducing system operating costs and minimizing power losses. By applying optimization methods, this study aims to produce a generator loading scheme that ensures efficiency while maintaining system reliability.

The OPF problem is addressed under peak load conditions using two metaheuristic optimization algorithms, namely Particle Swarm Optimization (PSO) and Simulated Annealing (SA). Both algorithms are used because the PSO algorithm has several weaknesses, such as premature convergence to the local optimum. One of the reasons is that all particles have a tendency to fly to the current best solution which is the local optimum or a solution close to the local optimum, so that all particles will be concentrated in a small particle region and the global exploration capability will be weakened. The character of the SA algorithm is a probabilistic algorithm, namely a worse solution has a probability of being accepted as a new solution, therefore, by combining the PSO and SA algorithms, the weaknesses of PSO can be improved with its jump feature. In other words, the PSO algorithm is often stuck in local optima and cannot converge to the global optimum. This weakness is considered the weakest point in the PSO algorithm.

The PSO-SA algorithm is used to determine the optimal generation output for each unit, and the results are compared with actual operational data from PT PLN's NTB Regional Main Unit. This comparative analysis aims to assess the effectiveness of heuristic optimization in real-world system operation and to identify potential cost-saving strategies for the Lombok network.

Previous research has demonstrated the potential of PSO in solving multi-objective OPF problems, such as a 2019 study on wind-integrated power systems that incorporated demand response programs **(Ma et al., 2019)**. That work proposed an economic scheduling model aimed at minimizing both generation costs and carbon emissions. More recently, in 2022, a study developed a dynamic OPF framework based on scheduling to optimize grid-scale Battery Energy Storage Systems (BESS), targeting improved renewable energy utilization and reduction of network demand fluctuations **(Fan et al., 2022)**. These contributions highlight the evolving application of OPF methodologies in addressing the challenges of modern power systems, forming the basis for the hybrid PSO-SA approach explored in this study.

2. METHODOLOGY

In this study, Optimal Power Flow (OPF) calculations were tested using a hybrid Particle Swarm Optimization–Simulated Annealing (PSO-SA) algorithm, with the Lombok power system as the research object. The power system includes seven fossil fuel-based power plants, namely Jeranjang Coal Power Plant, Sambelia Coal Power Plant, Ampenan Diesel Power Plant, Taman Diesel Power Plant, Sewatama Jeranjanjang, Cogindo Pringgabaya, and Paok Motong Diesel Power Plant. The total installed capacity of all power plants reaches 319.86 MW, with a peak system load of 193.34 MW. Based on their characteristics, the seven power plants can be categorized into two main types, namely diesel power plants and turbine power plants.

2.1 Lombok Radial Electrical System

The Lombok electricity system, which is the subject of this study, is a radial configuration system consisting of seven power plants and 19 buses. To simplify the computation and analysis process, a line diagram was drawn and then further simplified. The results of the diagram simplification are presented in Figure 1.

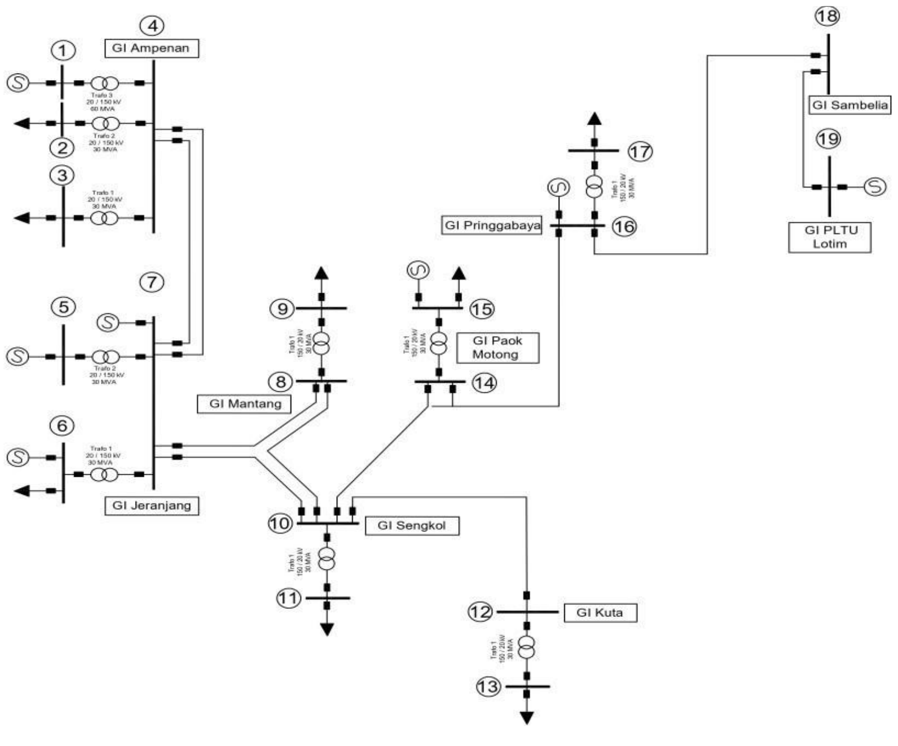

Figure 1. One Line Diagram of The Lombok Electrical System

Each generator in the system has its own technical specifications. Those specifications are summarized in Table 1. This data was obtained from the processed operational data of PT PLN (Persero) UP3B Mataram. Table 1 describes the generator units connected to each bus along with the total generation capacity at that bus.

This generation data will then be used to calculate the cost coefficient and perform an Optimal Power Flow (OPF) simulation. It should be noted that the generation value at the slack bus (defined as bus 1) has not been determined at this stage, as it will be a variable resulting from the power flow calculation process.

Table 1. Lombok System Generator Data

BUS	GENERATOR	POWER (MW)	CAPACITY (MW)
1	AMP Diesel Power Plant	55.76	79.66
5	SWTM Diesel Power Plant	18.83	22
6	SWTM Diesel Power Plant 3	1.96	8.8
7	JRJ Coal-Fired Power Plant	36.89	90
15	PKM Diesel Power Plant	15.51	23.4
16	PLTD COG	33.43	41
19	SBL Coal-Fired Power Plant	50	60
Total		199.34	319.86

In addition to generator and load specifications, transmission line characteristics are also critical parameters. The specifications of the 150 kV Lombok system transmission lines are presented in Table 2. The line impedance (Z) for modeling is obtained from the positive sequence impedance (Z1) value, which is identical. However, the Z1 value in Table 2 is the value per kilometer. Therefore, to obtain the impedance of each line individually, the Z1 value must be multiplied by the length of each line. The results of the impedance value calculations for each line in the Lombok power system (Figure 1) are then summarized in Table 3. The line length data used in these calculations is sourced from PT PLN (Persero) UP3B Mataram.

Table 2. Transmission Line Specifications for the Lombok Electrical System

Conductor Type	ACSR Hawk
Cross-sectional Area	240 mm²
Z_1& Z_2	(0.137+j0.4095) Ω/km
Z_0	(0.33933+j0.94228) Ω/km

Table 3. Data for each line in the Lombok Electrical System

Line Number	Bus		Line Impedance (Ω/km)	Line Length (km)	Line Parameters (pu)*	
	From	To			R	X
4	4	7	0.137+j0.4095	7.11	0.0043292	0.0129402
7	7	8	0.137+j0.4095	36.19	0.022035689	0.0658658
8	7	10	0.137+j0.4095	38.45	0.023411778	0.069979
10	8	10	0.137+j0.4095	31.19	0.018991244	0.0567658
12	10	12	0.137+j0.4095	12.00	0.007306667	0.02184
13	10	14	0.137+j0.4095	38.99	0.023740578	0.0709618
16	14	16	0.137+j0.4095	17.66	0.010752978	0.0321412
18	16	18	0.137+j0.4095	17.28	0.0105216	0.0314496
19	18	19	0.137+j0.4095	1.44	0.000876034	0.00261850

2.2 Economic Dispatch Formulation

Economic dispatch is a fundamental optimization approach in power system operation that determines the most economical allocation of generation among available units to satisfy the system load at the lowest possible cost. The primary objective is to identify the output of each generating unit in such a way that the total production cost is minimized while maintaining reliable operation. Since each generator is characterized by specific operational features influenced by factors such as fuel type, conversion efficiency, and design, the overall cost function varies across units. These unique characteristics lead to diverse cost functions that must be accounted for in the optimization process, thereby ensuring an accurate and efficient dispatch strategy **(Marzbani & Abdelfatah, 2024)**.

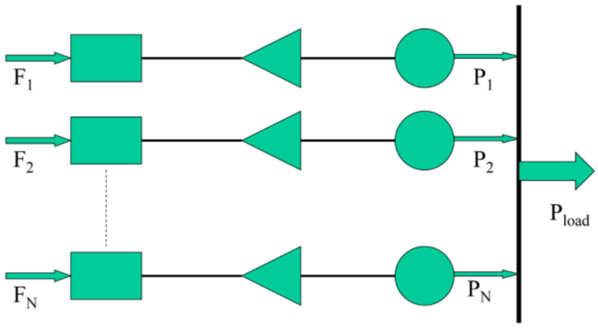

Figure 2. System With N Generating Units Without Transmission Losses

To illustrate this concept, Figure 2 depicts a simplified thermal power generation system composed of N generating units connected to a common bus bar. The bus supplies the total system demand, denoted as P_{Rbeban}, which must be met collectively by all generating units. For each unit i, the input is represented by F_i, describing the fuel cost function, while the corresponding output, P_i, denotes the electrical power produced. The overall operating cost of the system, expressed as F_T, is the cumulative sum of the costs associated with each generating unit. This structure highlights the interdependence between individual unit performance and the aggregate economic outcome of the entire system.

A critical operational constraint in economic dispatch requires that the sum of the power outputs from all generating units must equal the total system demand. In the simplest case, where transmission losses are neglected and unit-specific operating constraints are not explicitly considered, the problem formulation becomes a straightforward optimization model. The objective is to minimize the total generation cost function, F_T, while ensuring compliance with the equality constraint that enforces power balance. This mathematical representation, as presented in Equation (1), forms the basis of the economic dispatch model, serving as a foundational element in modern power system optimization and planning.

$$F_T = F_1 + F_2 + F_3 + \ldots + F_n \tag{1}$$

2.3 Optimal Power Flow (OPF)

The OPF formulation expands the scope of classical load flow analysis by embedding optimization objectives, typically aimed at minimizing generation cost while respecting system constraints. This formulation is not only limited to fulfilling power balance constraints, but also aims to optimize parameters such as total power plant operating costs **(Ali et al., 2024)**. The goal is to obtain an economical power generation configuration while still considering network losses **(Sultan et al., 2025)**. Essentially, OPF represents a nonlinear optimization problem in which the power output of each generator must be determined within its operating limits to meet demand at the lowest possible production cost, while adhering to technical requirements such as generation capacity limits, bus voltage ranges, and transmission line thermal limits **(Saadat, 1999)**. In this context, OPF can be understood as a comprehensive integration of economic dispatch and power flow analysis, with the generator cost function for unit i generally expressed in quadratic form, as formulated in Equation (2).

$$Min\ (F_i) = \sum_{i=1}^{Ng} a_i\, Pg_i^2 + b_i Pg_i + c_i \ \$/hour \quad (2)$$

2.4 Constraints

The calculation of optimal power flow has constraints that must be met. These constraints include the following **(Gopinath & Meher, 2018)**.

a. *Equality Constraint*

$$\sum_{i=1}^{Ng} Pg_i = Pg + PL \quad (3)$$

In the Optimal Power Flow (OPF) formulation, system operational constraints are classified into two main types. First are the equality constraints, which ensure compliance with the principle of power balance (conservation) by requiring that the total generated power equals the sum of the total load and all system transmission losses. The equality constraints are shown in Equation (3).

b. *Inequality Constraint*

$$P_{i\,min} \leq Pg_i \leq P_{i\,max} \quad (4)$$

$$Q_{i\,min} \leq Qg_i \leq Q_{i\,max} \quad (5)$$

Inequality constraints limit the output power of each generating unit to remain within the permissible/feasible operating range, i.e., not exceeding the maximum limit and not falling below the minimum limit of its generation capacity. The mathematical model of these constraints is shown in Equations (4) and (5).

2.4 Particle Swarm Optimization (PSO)

To address highly complex and nonlinear optimization problems such as Optimal Power Flow (OPF), one of the most commonly applied approaches is Particle Swarm Optimization (PSO). Originally proposed by Kennedy and Eberhart in 1995, PSO is an evolutionary computation technique rooted in swarm intelligence, inspired by the collective foraging behavior of bird flocks **(Freitas et al., 2020; Gad, 2022)**. In this algorithm, every potential solution is represented by a particle that navigates through the multidimensional search space. The trajectory of each particle is influenced by two essential learning components: the best position reached by the particle itself, referred to as Pbest (particle best), and the best position identified by the entire population, referred to as Gbest (global best) **(Santosa & Willy, 2011)**. Through repeated interactions and iterative updates, the swarm gradually converges towards an optimal or near-optimal solution, as conceptually depicted in Figure 3.

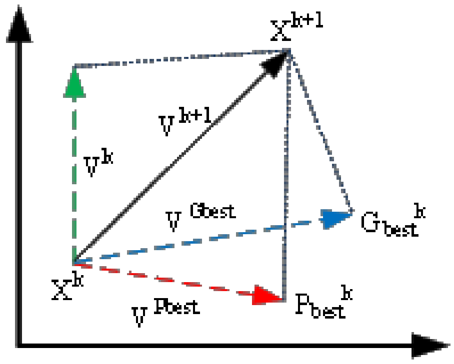

Figure 3. Concept of Pbest and Gbest Search in PSO

The dynamic search process in PSO relies on updating the velocity and position of particles. Each particle is modeled as an intelligent agent that adjusts its path by integrating two sources of information: its own cognitive memory (Pbest), which reflects individual learning, and the social influence derived from the experiences of other particles in the swarm (Gbest). This balance between self-exploration and social cooperation enhances the swarm's ability to escape local optima and efficiently navigate toward the global optimum. The movement update equations shown in Equations (6) and (7), which form the mathematical foundation of PSO, govern how particles iteratively refine their positions within the solution space by combining these cognitive and social factors.

$$v_i^{t+1} = wv_i^t + c_1 r_1^t (Pbest_i^t - x_i^t) + c_2 r_2^t (Gbest^t - x_i^t) \tag{6}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{7}$$

Within the context of this study, PSO is specifically applied to optimize generation dispatch with the dual objectives of minimizing fuel costs and reducing transmission losses while rigorously adhering to OPF constraints. Each particle corresponds to a potential solution consisting of generator outputs subject to operational limits. Parameters such as maximum iterations define the number of computational cycles executed, whereas cognitive and social constants regulate the balance between exploration and exploitation. By integrating these mechanisms, the PSO framework provides a powerful and flexible optimization tool capable of delivering reliable, cost-effective, and technically feasible solutions for modern power system operation.

2.5 Simulated Annealing (SA)

Simulated Annealing (SA) is a metaheuristic optimization technique inspired by the physical annealing process in metallurgy, where a material is subjected to controlled heating and gradual cooling to enhance its crystalline structure and mechanical stability **(Suman & Kumar, 2006)**. The fundamental strength of SA lies in its ability to escape local optima by probabilistically accepting inferior solutions, thereby promoting a more extensive exploration of the search space **(Alkhamis & Hosny, 2023)**. At higher temperatures, the algorithm explores broadly, mimicking the free movement of high-energy atoms. As the temperature decreases in accordance with the cooling schedule, the search becomes more exploitative, allowing the algorithm to refine candidate solutions and converge towards the global optimum, which represents the lowest energy—or best objective function—state.

The general procedure of the SA algorithm begins with the initialization phase, where parameters such as the initial temperature (T) and final temperature (Tθ) are determined, followed by the random generation of an initial solution (Ci) and the evaluation of its objective function f(Ci). The iterative process then commences, in which new candidate solutions (Ci') are generated through slight modifications of the current solution. Each candidate is evaluated, and acceptance is determined based on criteria that allow not only superior solutions but also inferior ones with a probability $P=\exp(-\Delta f/T)$, where Δf represents the change in objective function. This probabilistic acceptance mechanism is governed by a random number $r \in [0,1]$, ensuring controlled stochasticity in the search process. After each iteration, the temperature is reduced following a predetermined cooling schedule. The algorithm terminates when the current temperature falls to or below Tθ, at which point the optimal or near-optimal solution is obtained.

2.4 Hybrid PSO-SA Algorithm

Although effective, the PSO algorithm has an inherent weakness in that it tends to converge prematurely to a local optimum **(Nikolaev & Jacobson, 2010)**. This occurs because all particles tend to gather in the best solution region found at that time, which may not be the global solution, thereby weakening the algorithm's exploration capabilities.

In contrast, the probabilistic nature of the SA algorithm allows it to accept temporarily worse solutions, giving it a strong ability to escape local optima. Therefore, this study proposes the integration of both algorithms in a hybrid framework called PSO-SA. At each iteration, the best solution produced by PSO is used as the initial solution for the SA process. Annealing simulation then helps expand the search and increase the probability of finding a global solution, thereby overcoming the main weakness of PSO. The implementation of this hybrid scheme is shown in Figure 4.

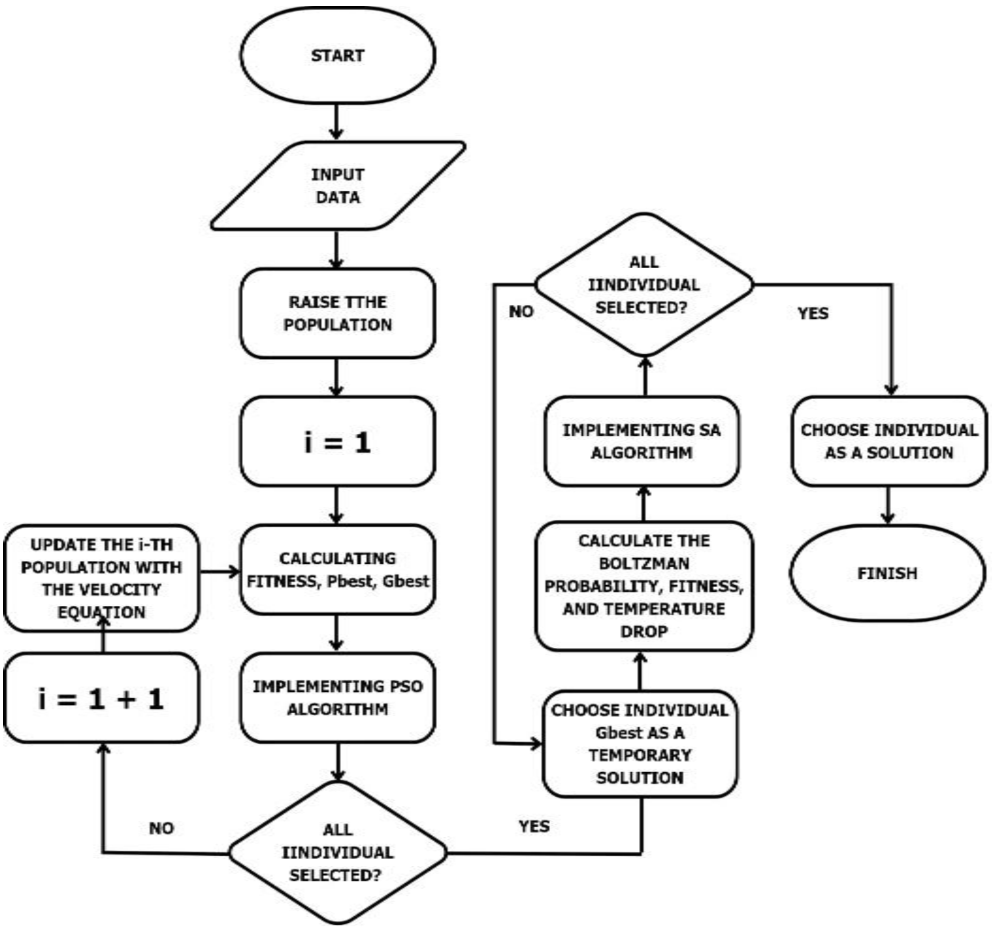

Figure 4. PSO-SA Flowchart

3. RESULTS AND DISCUSSION

3.1 OPF Simulation Using PSO-SA

The network configuration comprises twelve load buses distributed across both sides of the transformer at voltage levels of 20 kV and 150 kV, thereby representing the hierarchical structure of the system. Additionally, the system is supported by six generator buses and one slack bus, ensuring a balanced and stable operation during optimization. The initial setup, including detailed parameters of all buses under peak load conditions, is comprehensively presented in Table 4, serving as the foundation for the subsequent optimization process.

Table 4. Bus Settings and Electrical Load in Lombok during Peak Load

Bus Number	Bus Type	P_G (MW)	Q_G (MVAr)	P_D (MW)	Q_D (MVAr)
1	Slack Bus	-	-	57.15	9.548
2	Load Bus	0	-	28.70	3,847
3	Load Bus	0	0	0	0
4	Generator Bus	21.49	-	0	0
5	Generator Bus	1.96	-	16.01	2,173
6	Generator Bus	36.89	0	0	0
7	Load Bus	0	0	0	0
8	Load Bus	0	0	19.57	2,104
9	Load Bus	0	0	0	0
10	Load Bus	0	0	16.12	2,493
11	Load Bus	0	0	0	0
12	Load Bus	0	0	19.12	0.728
13	Load Bus	0	0	0	0
14	Generator Bus	16.60	-	26.75	2,841
15	Generator Bus	33.43	-	0	0
16	Load Bus	0	-	9.92	0.621
17	Load Bus	0	0	0	0
18	Generator Bus	50.08	-	0	0

During the testing phase, the Optimal Power Flow (OPF) was solved using the hybrid PSO-SA approach. Prior to executing the simulation, the minimum (Pmin) and maximum (Pmax) generation capacities of all generators were determined, as documented in Table 5, to define the operating boundaries of each generating unit. Furthermore, the cost coefficients of each generator, which form the basis of the objective function for minimizing generation costs, were carefully evaluated and are reported in Table 6. These preparatory steps ensured that the optimization process accurately represented the technical and economic constraints of the system, thereby enabling the PSO-SA method to effectively identify the most economical and reliable generation dispatch solution under peak operating conditions.

Table 5. Generator Capacity

Generator	Pmin (MW)	Pmax (MW)
Generator 1	5	79.66
Generator 2	5	22
Generator 3	1.5	8.8
Generator 4	5	90
Generator 5	5	23.4
Generator 6	5	35.2
Generator 7	5	60

Table 6. Generator Cost Function

Generator	a	b	c
Generator 1	1.54818	160.1961	1172
Generator 2	0.09776	278.1519	25
Generator 3	2.58888	339.2166	2.5
Generator 4	0.00762	50.36437	1
Generator 5	1.76106	250.8115	87.2
Generator 6	0.35572	122.3283	85.1
Generator 7	0.19717	599.9980	1999

3.2 Generation Cost Analysis

The Optimal Power Flow (OPF) analysis conducted in this study emphasizes the dual objectives of minimizing both generation costs and power losses. The performance of the optimization is comprehensively summarized through critical variables, including total generation cost, transmission losses, individual generator outputs, and total generated power, which are systematically presented in Table 7. These parameters serve as a benchmark for assessing the effectiveness of the applied optimization approach in improving the efficiency and reliability of system operation.

The results reveal that the total power generation reached 193.736 MW, a value that corresponds precisely to the sum of overall load demand and the anticipated transmission losses. This outcome validates that the equality constraint, which requires strict adherence to the balance between generation and demand, has been fully satisfied. Additionally, all generator units were observed to operate within their permissible power output limits, bounded by minimum (P_{min}) and maximum (P_{max}) thresholds. Notably, several units—specifically Generating Unit 3, Generating Unit 4, and Generating Unit 6—were identified to operate precisely at their respective boundaries, either at maximum or minimum capacity. The distribution profile of active power output across all generating units is illustrated in Figure 5, providing further insights into system behavior under optimized conditions.

In parallel, the convergence performance of the hybrid PSO-SA algorithm is demonstrated in Figure 6. The curve indicates that convergence was successfully achieved at the 140th iteration, well before the completion of the total 200 iterations executed during the optimization process. This early convergence highlights the efficiency and robustness of the algorithm in obtaining the optimal solution to the OPF problem, ensuring both computational effectiveness and practical applicability for real-world power system optimization.

Table 7. OPF Simulation Results Using the PSO-SA Method

Generator	Power (MW)	Load (MW)	Losses (MW)	Cost
Generator 1	39.09			
Generator 2	14.15			
Generator 3	1.5			
Generator 4	90	193.34	0.396	$ 31158
Generator 5	8.7			
Generator 6	35.2			
Generator 7	5.00			
Total	193.736			

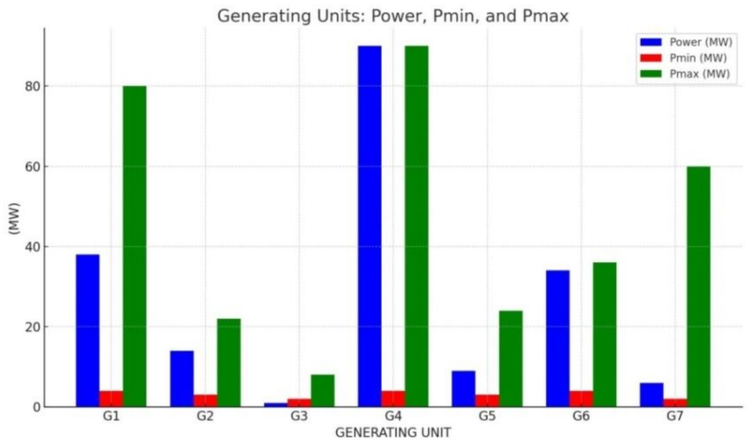

Figure 5. Power Generation Curve

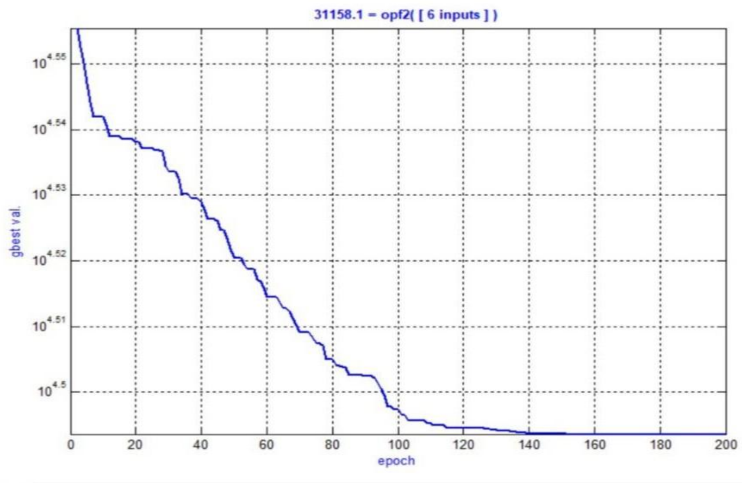

Figure 6. PSO-SA Convergence Characteristic

3.3 Voltage Profile of Buses

The results of the voltage profile simulation for each bus are depicted in Figure 7. The graphical representation shows that the voltage magnitudes across the network are consistently within the permissible operating range of 0.95 to 1.05 per unit (pu). In particular, some buses, such as buses 1, 15, 18, and 19, show voltage levels close to the upper threshold of the set operational margin, highlighting their proximity to the maximum permissible limit. The overall analysis verifies that all buses comply with the established voltage regulation criteria, thus confirming the adequacy of system voltage stability under the given operating scenario.

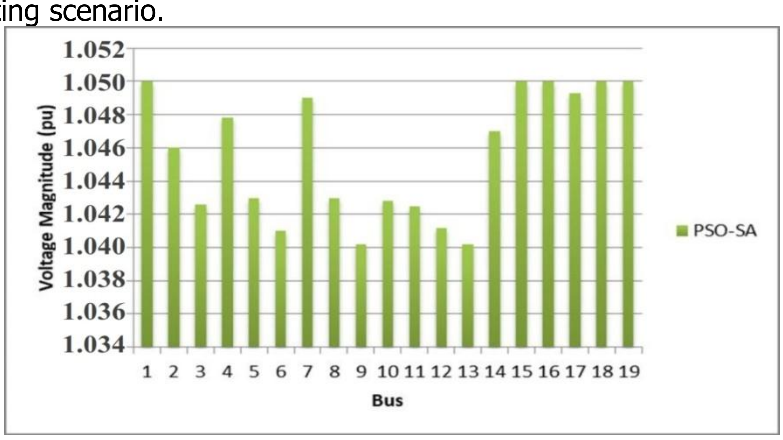

Figure 7. Bus Voltage Curve

3.4 Power Flow in Transmission Lines

The results of the power flow simulation on each transmission line are shown in Table 8 and Figure 8. The analysis shows that the power flow on lines 1 to 19 is still below the line capacity of 30 MVA to 180 MW.

The simulation results show that the power flow on channel 1 has the lowest power flow value, which is 0.31 MW, while channel 4 recorded the highest power flow value of 46.71 MW. A visualization comparing the power flow and thermal capacity of each channel is presented in Figure 8. These results confirm that the power flow on all channels is below its maximum capacity limit, indicating that the channel capacity constraint has been met.

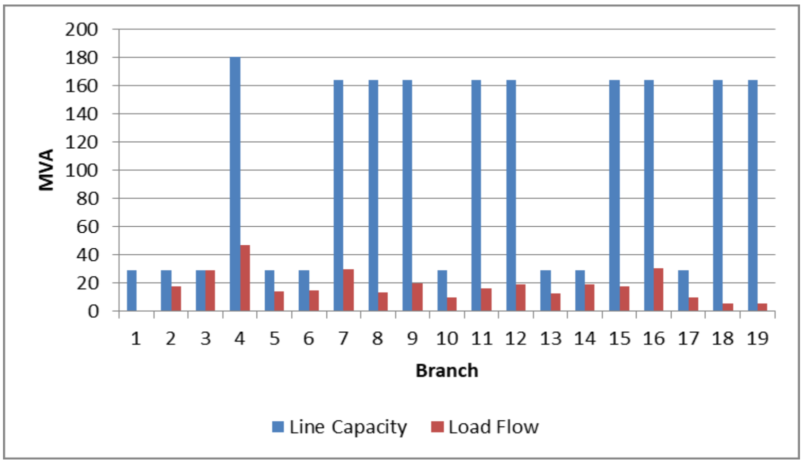

Figure 8. Flow Value Curve in Each Branch

Table 8. Power Flow in Each Branch

Branch	Bus		From		To	
	From	To	P (MW)	Q (MVAR)	P (MW)	Q (MVAR)
1	1	4	-0.31	3.75	0.31	-3.74
2	2	4	-17.70	-2.86	17.70	3.05
3	3	4	-28.70	-3.87	28.70	4.83
4	4	7	-46.71	-4.13	46.71	4.26
5	5	7	13.98	-4.83	-13.98	5.08
6	6	7	-14.51	-6.30	14.51	6.58
7	7	8	29.48	-0.02	-29.48	0.07
8	7	10	13.24	5.39	-13.24	-5.26
9	8	9	19.57	2.55	-19.57	-2.10
10	8	10	9.73	-2.62	-9.73	2.67
11	10	11	16.12	2.80	-16.12	-2.49
12	10	12	19.14	1.87	-19.14	-1.13
13	10	14	-12.35	-2.08	12.35	2.19
14	12	13	19.12	1.13	-19.12	-0.73
15	14	15	17.80	-2.74	-17.80	3.09
16	14	16	-30.19	0.56	30.19	-0.29
17	16	17	9.92	0.73	-9.92	-0.62
18	16	18	-5.00	0.83	5.00	-0.83
19	18	19	-5.00	0.83	5.00	-0.83

3.5 Comparison of Actual Costs with the PSO-SA Algorithm

Table 9. Comparison of Generation Costs

Method	Cost (USD)	Cost (Rp)
Actual	31,754	476,310,000
PSO-SA	31,158	467,370,000

As the final part of the comparative analysis, Table 10 presents a comparison of generation costs between actual conditions and optimization results using the PSO-SA algorithm. Based on Table 9, the simulation with the PSO-SA algorithm produces the lowest generation cost, which is $31,158. This value is lower than the generation cost under actual conditions, which was recorded at $31,754. Thus, it can be concluded that the implementation of the PSO-SA hybrid algorithm successfully optimizes the Optimal Power Flow (OPF), as evidenced by a significant reduction in electricity generation operating costs compared to the existing system operation.

4. CONCLUSION

The conducted simulations convincingly demonstrate that the hybrid Particle Swarm Optimization–Simulated Annealing (PSO-SA) technique is a robust and efficient tool for addressing the Optimal Power Flow (OPF) problem in the Lombok power network. All operational requirements of the system are successfully fulfilled, with the equality constraint achieved through a precise balance between the total generation output of 193.736 MW and the overall demand plus system losses. Likewise, the inequality conditions are fully satisfied, as reflected in the well-regulated bus voltage profile consistently maintained within the acceptable margin of 0.95–1.05 pu, alongside the absence of any transmission line overloading, thus ensuring secure system operation under the proposed optimization framework. From an economic and technical perspective, the PSO-SA algorithm demonstrates clear superiority by yielding the minimum generation cost of $31,158, which represents a substantial reduction compared with the actual operating expenditure of $31,754 under existing conditions. Moreover, the algorithm successfully minimizes real power losses to only 0.396 MW, further contributing to operational efficiency. These comprehensive results underline the effectiveness of the proposed hybrid approach in not only reducing generation costs but also reinforcing system reliability, efficiency, and stability.

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