

Optimal Solar PV Capacity Planning in Bangka Power System Using Grey Wolf Optimizer

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ABSTRACT

This study develops a simplified optimization-based framework to determine the optimal Solar Photovoltaic (PV) capacity for the Bangka power system by combining an annual cost-minimization model with the Grey Wolf Optimizer (GWO). Annual electricity demand is supplied by PV and system-level fossil-based generation, while total annual cost comprises annualized PV investment, PV operation and maintenance (O&M), and fossil generation costs. Three scenarios are evaluated: a baseline without PV, a fixed-PV capacity of 50 MW, and a GWO-optimized PV capacity bounded between 0 and 150 MW. The calculations and GWO procedure are implemented in Python 3.10 using 30 wolves, 100 iterations, and 20 independent runs. All runs converge to the upper feasible capacity of 150 MW. At this capacity, PV generation reaches 236.52 GWh/year, representing 15.6% of annual electricity demand, compared with 78.84 GWh/year or 5.2% in the fixed-PV scenario. Fossil generation cost decreases from 181.73 to 153.35 million USD/year. After including 13.75 million USD/year in annualized PV investment and 2.25 million USD/year in PV O&M costs, the total annual system cost reaches 169.35 million USD/year, yielding net savings of approximately 12.38 million USD/year relative to the baseline. Annual CO₂ emissions decrease from 1211.54 to 1022.32 ktCO₂/year, corresponding to a reduction of approximately 189.22 ktCO₂/year. Within the adopted annual model assumptions, the 150 MW configuration provides the lowest cost and emissions among the evaluated alternatives and represents a boundary optimum.



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1. INTRODUCTION

The increasing demand for electricity, combined with the need to reduce greenhouse gas emissions, has accelerated the transformation of power systems worldwide [1]. In many developing regions, including Indonesia, electricity generation remains largely dependent on fossil fuel-based technologies, particularly coal and diesel power plants [2]. This dependency leads to high operational costs due to fuel consumption and contributes significantly to carbon emissions [3]. Therefore, integrating renewable

energy into existing power systems has become an essential strategy to support sustainable and low carbon energy transitions.

Regional and island power systems present distinct challenges compared to large interconnected grids [4]. The Bangka Belitung power system, for instance, operates as a semi-isolated system with limited interconnection capacity and a strong reliance on local generation units. Based on recent system data, the total installed capacity in the Bangka system is approximately 242 MW without transfer and increases to about 342 MW with power transfer from Sumatra. The system peak load reaches around 225 MW, indicating relatively tight operational margins [5]. In addition, a significant portion of generation is still supplied by diesel and small-scale thermal units, which are characterized by high fuel costs and emissions. These characteristics make the system particularly sensitive to changes in generation mix and highlight the importance of optimal capacity planning.

Solar Photovoltaic (PV) represents a promising renewable energy option for the Bangka Belitung region due to the high total solar irradiance in the Bangka Belitung Islands, which reaches approximately 4.95 kWh/m² day [6], as well as its modular deployment capability. The average daily load profile shows a peak demand of approximately 198.89 MW and annual energy consumption of about 1514.42 GWh [5], indicating a substantial opportunity for integrating solar based generation. However, determining the appropriate capacity of PV integration remains a critical challenge. Excessive PV capacity may lead to curtailment [7] or operational inefficiencies [8], while insufficient capacity may not significantly reduce fossil fuel dependency [9]. Therefore, an optimization-based approach is required to determine the optimal PV capacity that balances cost, reliability, and environmental performance.

Optimization techniques have been widely applied in power system planning to identify cost effective solutions [10]. While conventional optimization methods are effective for structured problems, they may become less flexible when dealing with nonlinear relationships and complex search spaces [11]. In this context, metaheuristic algorithms offer a practical alternative due to their simplicity and ability to explore a wide range of solutions [12]. Among these approaches, the Grey Wolf Optimizer (GWO) is a nature inspired metaheuristic algorithm that simulates the social hierarchy and cooperative hunting behavior of grey wolves [13]. The algorithm has attracted considerable attention in engineering optimization because of its strong convergence capability, balanced exploration and exploitation mechanisms, and ease of implementation [14].

This study aims to determine the optimal Solar PV capacity for the Bangka Belitung power system using the GWO and to evaluate its impact on system cost, fossil fuel consumption, and CO₂ emissions. Three scenarios are investigated, namely the baseline system without PV integration, a fixed PV capacity scenario, and a GWO-optimized PV capacity scenario. By focusing on a regional island power system with real operational characteristics, this study provides practical insights into renewable energy integration and system efficiency improvement. The remainder of this paper is organized as follows. Section 2 describes the proposed methodology, including the system model, mathematical formulation, and GWO algorithm. Section 3 presents and discusses the optimization results, while Section 4 concludes the study by summarizing the main findings and their implications for regional power system planning.

2. RESEARCH METHOD

An optimization-based framework is developed to determine the optimal Solar PV capacity for the Bangka power system by integrating a cost-minimization model with the GWO. The framework incorporates the objective function, system constraints, optimization procedure, and performance indicators to evaluate the economic and environmental performance of the optimized system.

2.1. Problem Formulation

This study addresses the determination of the optimal Solar PV capacity for the Bangka power system within a cost-minimization framework. The system is represented by a simplified annual aggregated model in which electricity demand is assumed to be known over the planning period and is supplied by two generation sources, namely Solar PV and fossil-fuel-based generation. This representation captures the fundamental trade-off between renewable energy integration and conventional generation while maintaining computational efficiency. The installed PV capacity, K_{PV}

(MW), is treated as the primary decision variable, whereas conventional generation operates as the balancing source to satisfy the remaining demand.

The annual electricity demand is denoted by E_{demand} (GWh/year), while PV generation, E_{PV} , is determined by the installed PV capacity, the PV capacity factor (CF_{PV}), and the annual operating hours (H). Fossil generation, E_{fossil} , supplies the unmet demand after accounting for PV generation, thereby ensuring energy balance throughout the planning horizon. Based on this formulation, the optimization problem evaluates the economic performance of different PV capacity levels and is subsequently solved using the GWO, as described in the following sections.

2.2. Objective Function

The optimization problem aims to minimize the total annual system cost, which represents the combined economic impact of Solar PV installation and fossil based electricity generation [15]. The total cost consists of three main components, namely the annualized PV investment cost, PV operation and maintenance cost, and fossil generation cost, as expressed in Eq. (1). This formulation captures the economic interaction between capital intensive renewable deployment and variable cost conventional generation. The objective function is expressed in annual monetary terms to ensure consistency among all cost components. As a result, the optimization identifies the most cost effective balance between PV integration and fossil based generation.

$$C_{\text{total}} = C_{PV, \text{ann}} + C_{PV, O\&M} + C_{\text{fossil}} \quad (1)$$

In Eq. (1), C_{total} denotes the total annual system cost expressed in USD/year. The first component, $C_{PV, \text{ann}}$, represents the annualized investment cost of Solar PV and is defined in Eq. (2). This cost converts the upfront capital expenditure (CAPEX) into an equivalent annual value using the capital recovery factor. The second component, $C_{PV, O\&M}$, accounts for the annual operation and maintenance cost of PV systems, as defined in Eq. (3). The third component, C_{fossil} , represents the cost of fossil-based electricity generation, which depends on the amount of fossil generation required to meet demand. Together, these components form a comprehensive representation of the system cost.

The annualized PV investment cost is calculated as:

$$C_{PV, \text{ann}} = K_{PV} \times CAPEX_{PV} \times CRF \quad (2)$$

In Eq. (2), K_{PV} is the installed PV capacity (MW), $CAPEX_{PV}$ is the capital cost (USD/MW), and CRF is the capital recovery factor (dimensionless). The multiplication of these terms results in a cost expressed in USD/year, which is consistent with Eq. (1). The use of annualized cost allows a fair comparison between investment and operational expenditures. This formulation ensures that long term capital costs are properly integrated into the annual cost structure. Therefore, Eq. (2) provides a realistic representation of PV investment cost within the optimization framework.

The PV operation and maintenance cost is defined as:

$$C_{PV, O\&M} = K_{PV} \times C_{PV}^{O\&M} \quad (3)$$

where $C_{PV}^{O\&M}$ is the O&M cost expressed in USD/MW/year. As shown in Eq. (3), the resulting unit is USD/year, which is consistent with Eqs. (1)-(2). This cost component captures the ongoing operational expenses associated with PV systems. Although typically smaller than capital costs, it contributes to the total system cost and must be included in the optimization. The linear relationship between capacity and O&M cost simplifies the formulation while maintaining accuracy. Thus, Eq. (3) ensures that operational costs are appropriately accounted for.

The fossil generation cost is calculated as:

$$C_{\text{fossil}} = E_{\text{fossil}} \times C_{\text{fossil}}^{\text{var}} \quad (4)$$

where E_{fossil} represents fossil-based electricity generation in MWh/year, while C_{fossil} denotes its system-level variable generation cost in USD/MWh. Fossil generation supplies the residual annual demand after accounting for PV generation; therefore, increasing PV capacity directly reduces fossil generation cost.

All cost components in Eq. (1) are expressed in consistent units of USD/year, ensuring dimensional coherence of the objective function. This consistency allows direct summation of all cost terms without additional conversion factors. The formulation establishes a clear relationship between capacity decisions and system cost. As a result, the optimization process can effectively identify the most economical level of PV integration. This objective function serves as the basis for evaluating and comparing different scenarios.

2.3. System Constraints

The optimization model is subject to a set of constraints that ensure the physical feasibility and operational consistency of the power system. These constraints describe the relationship between electricity demand, Solar PV generation, and fossil-fuel-based generation within an aggregated annual framework using consistent units. The primary constraint is the annual energy balance, which requires total electricity generation to satisfy annual electricity demand, as expressed in Eq. (5):

$$E_{PV} + E_{fossil} = E_{demand} \quad (5)$$

where E_{PV} , E_{fossil} , and E_{demand} are expressed in GWh/year. This equality ensures that all electricity demand is supplied without unmet demand or excess generation.

Solar PV generation is determined by the installed PV capacity, capacity factor, and annual operating hours, as given in Eq. (6):

$$E_{PV} = K_{PV} \times CF_{PV} \times H \quad (6)$$

where K_{PV} is the installed PV capacity (MW), CF_{PV} is the PV capacity factor, and H denotes the annual operating hours (8760 h/year). To ensure technical feasibility, the installed PV capacity is constrained within predefined limits:

$$0 \leq K_{PV} \leq K_{PV,max} \quad (7)$$

where $K_{PV,max}$ is the maximum allowable PV capacity (MW), representing practical limitations such as land availability, grid capability, and investment constraints.

Together, these constraints define the feasible search space explored by the optimization algorithm while maintaining energy balance and realistic PV deployment. Consequently, the optimization produces technically feasible and operationally consistent solutions for evaluating the economic and environmental performance of different PV integration levels.

2.4. Grey Wolf Optimizer

The optimization problem is solved using the GWO, a population-based metaheuristic inspired by the social hierarchy and cooperative hunting behavior of grey wolves. Each candidate solution represents an installed Solar PV capacity within the bounds defined in Eq. (7), and its quality is evaluated using the total annual cost objective in Eq. (1). During the optimization process, the three best candidate solutions are designated as the alpha (α), beta (β), and delta (δ) wolves. These leading wolves guide the remaining search agents toward promising regions of the solution space while maintaining a balance between exploration and exploitation.

The distance between a search agent and a leading wolf is calculated using Eq. (8), while the position of the search agent relative to that leader is updated using Eq. (9):

$$D = |C \cdot X_p - X| \quad (8)$$

$$X(t+1) = X_p - A \cdot D \quad (9)$$

where X is the current wolf position and X_p denotes the position of a leading wolf, namely α , β , or δ . The coefficient vectors A and C , which control the movement and search behavior of the wolves, are calculated using Eqs. (10) and (11), respectively:

$$A = 2ar_1 - a \quad (10)$$

$$C = 2r_2 \quad (11)$$

where r_1 and r_2 are random vectors in $[0, 1]$, while a decreases linearly from 2 to 0 throughout the iterations. This decreasing parameter gradually shifts the search from global exploration to local exploitation. Because the model contains one decision variable, the search space is one-dimensional and corresponds to the installed PV capacity, K_{PV} .

The influences of the alpha, beta, and delta wolves are combined to determine the updated position of each search agent using Eq. (12):

$$\begin{aligned} \mathbf{X}_1 &= \mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha \\ \mathbf{X}_2 &= \mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta \\ \mathbf{X}_3 &= \mathbf{X}_\delta - \mathbf{A}_3 \cdot \mathbf{D}_\delta \\ \mathbf{X}(t+1) &= \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3} \end{aligned} \quad (12)$$

In Eq. (12), D_α , D_β , and D_δ are calculated by applying Eq. (8) to the respective leading-wolf positions, while A_1 , A_2 , and A_3 are determined using Eq. (10). The updated wolf position is obtained from the average influence of the three leading wolves. After every update using Eq. (12), the candidate PV capacity is projected onto the feasible region defined in Eq. (7). The objective function in Eq. (1) is then reevaluated, and the process continues until the maximum number of iterations is reached. The best feasible solution at convergence is selected as the installed PV capacity that minimizes the total annual system cost.

2.5. Scenario Evaluation and Computational Implementation

All three scenarios were evaluated using the same annual model, input parameters, and calculation procedures defined in Eqs. (1)–(7). In the baseline scenario, K_{PV} was fixed at 0 MW; in the fixed-PV scenario, it was set to 50 MW; and in the GWO-optimized scenario, K_{PV} was treated as a decision variable bounded between 0 and 150 MW. For each scenario, annual PV generation was calculated using Eq. (6), fossil generation from the energy balance in Eq. (5), and total annual system cost from Eqs. (1)–(4). Annual CO₂ emissions were calculated from fossil electricity generation and the applicable emission factor. The baseline and fixed-PV scenarios were evaluated by direct substitution, whereas the optimized scenario was solved using the GWO implemented in Python 3.10. The GWO employed 30 wolves, 100 iterations, and 20 independent runs, with the lowest-cost feasible solution reported as the optimal PV capacity. Python 3.10 was also used to process the scenario outputs and generate the corresponding figures. To verify numerical accuracy, the GWO solution was cross-checked through direct evaluation of the objective function over the feasible PV-capacity range.

2.6. Input Data and Assumptions

The optimization model uses technical, economic, and algorithmic input parameters representing the annual characteristics of the Bangka power system, as summarized in Table 1. Annual electricity demand and system conditions are based on the Bangka power-system data reported in [5]. Electricity demand is supplied by Solar PV and fossil-based generation, with regional solar resource conditions represented by the PV capacity factor. The technology-cost and PV-lifetime assumptions are adapted from the Indonesian power-sector technology data in [16], while PV investment cost is annualized using a capital recovery factor based on the assumed discount rate and project lifetime. Fossil-based generation is represented using a single system-level variable cost and emission factor, with the emission-factor assumption based on [17], because the model evaluates annual capacity planning rather than unit-level generation dispatch. Within this formulation, chronological variations in electricity demand and generation and unit-level operational constraints are not explicitly modeled.

The installed PV capacity is bounded between 0 and 150 MW, while a capacity of 50 MW is adopted for the fixed-PV scenario. The use of an explicit capacity bound is consistent with the general formulation employed in generation-expansion planning studies [18]. The GWO is implemented using 30 wolves, a maximum of 100 iterations, and 20 independent runs. The lowest-cost feasible solution obtained across these runs is reported as the optimal PV capacity, and the resulting generation, cost, and emission indicators are compared with those of the baseline and fixed-PV scenarios.

Table 1. Input parameters used in the model [5, 16-18]

Parameter	Symbol	Unit	Value
Electricity demand	E_{demand}	GWh/year	1514.42
PV capacity factor	CF_{PV}	-	0.18
PV CAPEX	$CAPEX_{PV}$	USD/MW	960,000
PV O&M cost	$C_{PV}^{O\&M}$	USD/MW/year	7,500
Fossil generation cost	C_{fossil}	USD/MWh	120
Fossil emission factor	EF_{fossil}	tCO ₂ /MWh	0.8
Max PV capacity	$K_{PV,max}$	MW	150
Discount rate	r	-	0.1
PV lifetime	η	year	20
GWO population size	N	-	30
Max iterations	T	-	100
Number of runs	—	-	20

3. RESULTS AND DISCUSSION

The optimization results compare the baseline, fixed-PV, and GWO-optimized PV scenarios in terms of generation mix, total annual system cost, and CO₂ emissions. All figures were produced by the authors in Python 3.10 using outputs from the same annual model: generation was calculated using the energy-balance and PV-generation equations, total cost using Eqs. (1)–(4), and emissions using the fossil-generation-based emission calculation described in Subsection 2.3.

3.1. Electricity Generation Mix

The electricity generation mix across the three scenarios is presented in Figure 1. In the baseline scenario, PV generation is zero and the entire annual demand of 1514.42 GWh is supplied by fossil-based generation. The fixed-PV capacity of 50 MW generates 78.84 GWh/year, calculated as $50 \times 0.18 \times 8760/1000$, and supplies approximately 5.2% of annual electricity demand. Consequently, fossil generation decreases to 1435.58 GWh/year, representing 94.8% of demand. In the GWO-optimized scenario, the installed PV capacity of 150 MW generates 236.52 GWh/year and supplies approximately 15.6% of annual demand, while fossil generation decreases to 1277.90 GWh/year, representing 84.4% of demand.

Relative to the fixed-PV scenario, the optimized configuration increases annual PV generation by 157.68 GWh and raises its generation share from 5.2% to 15.6%, an increase of approximately 10.4 percentage points. This result demonstrates the direct displacement of fossil-based electricity by PV generation within the annual energy-balance model. Because calculated PV generation remains below annual electricity demand throughout the evaluated capacity range, no annual energy curtailment occurs, and fossil generation supplies the residual demand. Consequently, the reduction in fossil generation is directly proportional to the increase in PV output. Although fossil generation remains dominant, the optimized configuration provides the highest renewable contribution among the evaluated scenarios.

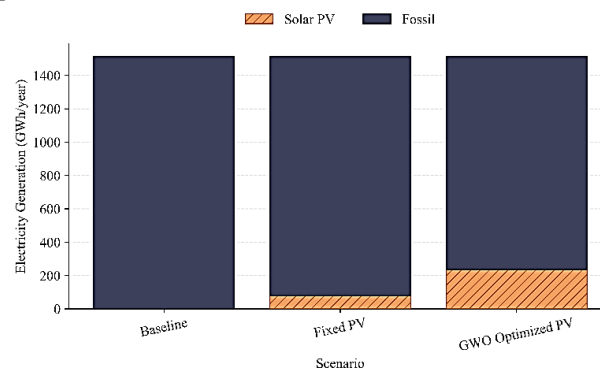


Figure 1. Electricity generation mix calculated from the annual energy-balance model

3.2. Cost Analysis

The annual system cost under each scenario is presented in Figure 2. The baseline cost of 181.73 million USD/year consists entirely of fossil generation cost because no PV capacity is installed. In the fixed-PV scenario, fossil generation cost decreases to 172.27 million USD/year, while annualized PV investment and O&M costs amount to 4.58 and 0.75 million USD/year, respectively. These components produce a total annual system cost of 177.60 million USD/year. In the GWO-optimized scenario, fossil generation cost decreases further to 153.35 million USD/year, while annualized PV investment and O&M costs reach 13.75 and 2.25 million USD/year, respectively. The resulting total cost is 169.35 million USD/year, corresponding to net savings of approximately 12.38 million USD/year relative to the baseline.

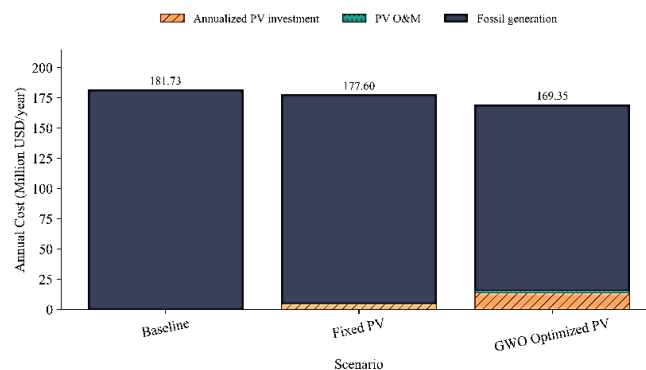


Figure 2. Annual system cost calculated from the model cost components

The cost reduction occurs because the avoided fossil generation cost exceeds the additional annual PV-related expenditure. Within the evaluated capacity range, each additional MW of PV incurs approximately 0.107 million USD/year in annualized investment and O&M costs but avoids approximately 0.189 million USD/year in fossil generation cost. Therefore, total annual system cost decreases by approximately 0.083 million USD/year for each additional MW of PV capacity. This negative marginal change in total system cost explains why the GWO selects the upper feasible capacity of 150 MW and independently corroborates the optimized solution under the adopted assumptions

3.3 Emission Analysis

The annual CO₂ emissions across the evaluated scenarios are presented in Figure 3. The baseline scenario produces 1211.54 ktCO₂/year because its entire electricity demand is supplied by fossil-based generation. Emissions decrease to 1148.46 ktCO₂/year in the fixed-PV scenario and to 1022.32 ktCO₂/year in the GWO-optimized scenario. These results correspond to annual emission reductions of approximately 63.07 and 189.22 ktCO₂/year, respectively, relative to the baseline.

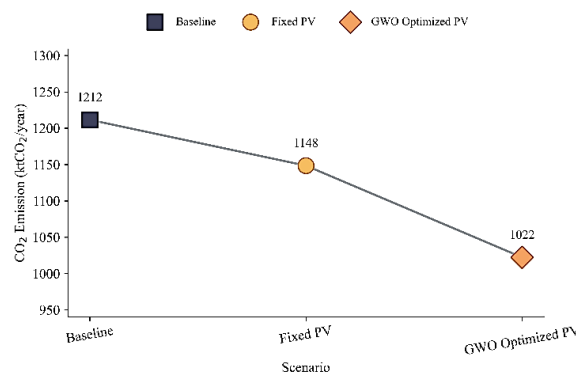


Figure 3. Annual CO₂ emissions calculated from fossil generation and its emission factor

The percentage reductions are approximately 5.2% for the fixed-PV scenario and 15.6% for the optimized scenario, consistent with their respective PV generation shares. This proportional relationship occurs because the model applies a constant fossil emission factor and assigns no operational CO₂

emissions to PV generation. Accordingly, within the adopted model boundary, emission mitigation is directly determined by the amount of fossil-based generation displaced by Solar PV. The optimized scenario provides the greatest environmental benefit because it achieves the largest reduction in fossil generation.

3.4. Cost and Emission Relationship

The relationship between total annual system cost and CO₂ emissions for PV capacities ranging from 0 to 150 MW is presented in Figure 4. Both indicators decrease consistently as PV capacity increases. Each additional MW of PV reduces total annual system cost by approximately 0.083 million USD/year and annual emissions by approximately 1.261 ktCO₂/year. Accordingly, solutions with higher PV capacities move toward the lower-cost and lower-emission region of the figure.

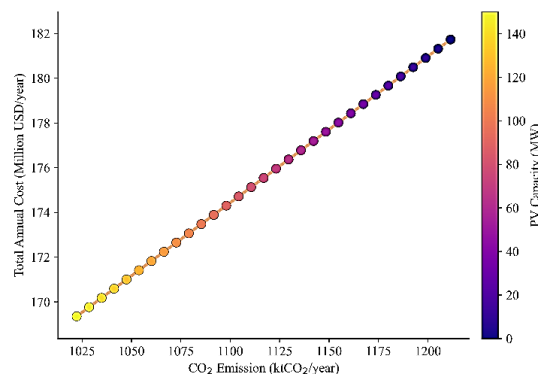


Figure 4. Cost and emission relationship across the evaluated PV-capacity range

No opposing economic-environmental trade-off occurs within the assumptions of the annual model because increasing PV capacity simultaneously reduces both indicators. Therefore, the 150 MW configuration dominates the lower-capacity alternatives and is identified as the boundary optimum. This result is conditional on the specified maximum PV capacity, constant PV capacity factor, adopted technology-cost and emission-factor assumptions, absence of modeled PV curtailment, and exclusion of chronological and unit-level operational constraints. Incorporating these factors into a more detailed model could produce nonlinear relationships or an interior optimum.

4. CONCLUSION

This study develops a simplified optimization-based framework to determine the optimal Solar PV capacity for the Bangka power system using the GWO. Under the adopted annual model assumptions, all GWO runs converge to the upper feasible capacity of 150 MW. At this capacity, PV generation reaches 236.52 GWh/year, representing approximately 15.6% of annual electricity demand, compared with 78.84 GWh/year or 5.2% in the fixed-PV scenario. Fossil generation cost decreases from 181.73 to 153.35 million USD/year; after accounting for approximately 16.00 million USD/year in annualized PV investment and O&M costs, the total annual system cost reaches 169.35 million USD/year. This result corresponds to net savings of approximately 12.38 million USD/year relative to the baseline. Annual CO₂ emissions also decrease from 1211.54 to 1022.32 ktCO₂/year, yielding a reduction of approximately 189.22 ktCO₂/year. Thus, within the evaluated capacity range, the 150 MW configuration provides the lowest system cost and emissions among the evaluated alternatives.

These findings provide system-level insights into the economic and environmental effects of PV capacity expansion in a regional power system where fossil-based generation remains dominant. However, the boundary optimum is conditional on the specified maximum PV capacity, constant PV capacity factor, adopted technology-cost and emission-factor assumptions, and absence of modeled PV curtailment. Because the annual model does not explicitly represent chronological variability, unit-level operation, network constraints, energy storage, or reliability requirements, the results should be interpreted as capacity-planning insights rather than evidence of operational feasibility. Future research may incorporate these elements to evaluate whether more detailed system conditions produce nonlinear relationships or an interior optimal PV capacity.

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