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Solar Power Integration Into the Transmission Network for Reducing Power Loss and Optimizing Generation Costs – A Comparative Analysis

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ABSTRACT

This paper investigates the integration of Solar Power Plants (SPP) into transmission grids through comparative assessment of two single-objective approaches: minimization of power loss and minimization of generation costs, while maintaining system operational safety conditions. Using the Particle Swarm Optimization algorithm on a modified IEEE 30-bus test system, the study sequentially determined the optimal SPP capacity and location for each objectives separately. The findings reveal that strategic placement and sizing are paramount, confirming that system benefits are non-linear with capacity increases and that the optimal bus location is highly site-specific. Crucially, comparative analysis demonstrates the clear superiority of the generation cost minimization objective. This economic-centric strategy not only achieves the largest reduction in total system cost but also concurrently provides superior technical performance by significantly reducing power losses. This dual success is achieved because the optimization algorithm exploits the locational value and zero-fuel-cost characteristic of solar power, inherently guiding the system toward an operating point that is both economically optimal and physically efficient. This research establishes a core principle for modern smart-grids: the most economically efficient design consistently delivers the most technically robust solution.

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1. Introduction

Rapidly growing global energy demand, evidenced by a 5% increase in total final energy consumption (TFEC) in 2022, is driving the accelerated development of renewable energy (RE). RE sources contributed 13% of global TFEC in 2022 [1]. Policy support across over 130 countries has fueled this trend, with RE capacity forecasted to reach 507 GW – a nearly 50% increase from 2022 levels [2]. Given the essential role of electricity in maintaining socio-economic and political stability, this burgeoning demand poses significant environmental and technical challenges for power systems [3]. Consequently, two paramount concerns for contemporary power system management are the minimization of power losses to enhance power quality and the optimization of generation costs to ensure competitive consumer pricing. Addressing these issues remains a global priority for energy managers and system planners.

Solar power plant (SPP) integration into transmission networks is an effective solution for reducing power losses and generation costs. Studies show that locating SPPs near load centers decreases active power losses, while their zero marginal cost helps replace expensive fossil-fuel generation, lowering total system costs [4]. Additionally, proper SPP placement improves voltage profiles, reduces infrastructure upgrade needs, and enhances system reliability [5]. However, inappropriate sizing or placement may increase losses, cause voltage violations, and create congestion [6]. Therefore, multi-objective Optimal Power Flow (OPF) methods are required to balance cost minimization and loss reduction, despite their inherent trade-offs [7].

The inherent variability of solar power necessitates a shift from deterministic to uncertainty-aware optimization models, as traditional OPF solutions may become infeasible in real-time operation. Stochastic Optimization (SO) uses probability-based scenarios to obtain an average optimal solution [8]. while Robust Optimization (RO) ensures security against worst-case uncertainties, commonly applied to unit commitment with high RE penetration despite its conservative nature [9]. A hybrid approach, Distributionally Robust Optimization (DRO), balances economic efficiency and robustness [10]. To address this complex, non-linear multi-objective problem, advanced algorithms continue to be developed. While AC, DC-OPF, and Security Constrained OPF (SC-OPF) remain essential, nature-inspired metaheuristics are critical for handling non-linearities and discrete variables [11]. Particle Swarm Optimization (PSO) is widely favored for its simplicity and computational efficiency [12], with recent focus on hybrid methods such as GWO-PSO (Grey Wolf Optimizer) [13]. Other metaheuristics, including Whale Optimization Algorithm (WOA) [14], Moth-Flame Optimization (MFO) [15], Artificial Bee Colony (ABC) [16], Differential Search Algorithms (DSA) [17], and Gravitational Search Algorithms (GSA) [18] have also been successfully applied. Beyond optimization, Energy Storage Systems (ESS) and Battery Energy Storage Systems (BESS) act as temporal buffers to achieve dual-objective targets [19]. Finally, Machine Learning (ML) and Artificial Intelligence (AI) further enable fast, data-driven OPF approximations, supporting near-real-time decisions [20], with Reinforcement Learning (RL) specifically explored for the dynamic optimal control of BESS and other grid assets [21].

Current research on SPP integration into transmission grids is categorized into three approaches: (1) single-objective optimization for power loss minimization; (2) techno-economic impact analysis; and (3) multi-objective optimization using Pareto-based techniques. Approach (1) emphasizes technical constraints due to their complexity, while Approach (3) seeks stakeholder agreement but may dilute individual optimality. Approach (2), though often overlooked, provides key insights by quantifying individual contributions to the objective function, considering grid configuration, natural conditions, and regional load characteristics [22], [23]. These problems are inherently nonlinear and complex, requiring extensive simulations across multiple configurations. PSO is selected due to its fast convergence and minimal parameter tuning, making it suitable for preliminary quantitative assessment. Although other metaheuristic or hybrid algorithms may improve global optimization accuracy, their higher computational cost and parameter sensitivity are unnecessary for this study [22].

This research addresses power loss reduction and generation cost optimization in a transmission system integrated with SPPs. The study evaluates SPP placement using two single-objective frameworks to achieve a technical–economic balance. The methodology applies PSO in MATLAB to analyze multiple SPP integration scenarios on the IEEE 30-bus system. The remain of the paper is structured as follows: Section 1 outlines the current status and prevailing challenges in power system operation. Section 2 details the PSO algorithm and the defined objective functions. Section 3 presents the case study simulations and analyses the obtained results. Finally, Section 4 offers conclusions and discusses the potential benefits of RE integration into the transmission grid.

2. Methodology

The PSO algorithm is employed to solve two distinct optimization problems: (1) Problem 1 seeks to determine the optimal PV penetration level that yields the minimum total power generation cost. The PSO iteratively identifies the lowest generation cost across loops; the corresponding PV generation capacity is accepted as the optimal solution only if it adheres to the predefined system penetration limit. The PSO settings for this problem are initialized with 100 populations and executed over 1000 iterations. (2) Problem 2 focuses on optimal PV source placement. With the number of distributed PV sources fixed at one, the grid is simulated, and the PSO algorithm recalculates the generation cost objective function to identify the installation location that results in the lowest total system generation cost. Using

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a parallel approach, PSO and PowerWorld were employed to determine the optimal installation location of the SPP for power loss minimization. The results are then incorporated into a comparative analysis to assess the efficacy of the defined objective functions.

2.1. Particle Swarm Optimization-PSO

The Particle Swarm Optimization (PSO) algorithm, pioneered by Eberhart and Kennedy in 1995, is a prominent metaheuristic within Swarm Intelligence (SI). Its design is inspired by emergent social behavior in decentralized systems, where collective problem-solving arises from localized interaction and shared learning. PSO is engineered to efficiently locate the optimal solution within a high-dimensional search space. The algorithm models a potential solution as a "particle", which navigates the search space driven by three key factors: (1) its own memory; (2) the collective knowledge of its neighbors; and (3) the global best-known position. The search process initiates in the Initial Phase, where a population of particles (solutions) is randomly distributed across the search space, each assigned a random initial position (x_i) and velocity (v_i). The core mechanism of PSO is the iterative adjustment of each particle's trajectory based on two primary sources of information: P_{best} (personal best) and G_{best} (global best). The P_{best} is the best position a particle i has achieved thoughout the search history, resulting in the most favorable fitness value (evaluated by the cost/objective function) $f(x_i)$. The G_{best} is the best position found so far by any particle in the entire swarm, corresponding to the overall lowest objective function value (CF_{best}). The Search Phase then proceeds, where each particle updates its velocity and position through a stochastic process balancing exploration and exploitation. This balance is essential to prevent premature convergence and ensure effective traversal of the search space.

The velocity and position update rules define the entire trajectory and optimization mechanism of the algorithm. In the Adjustment Phase, the new velocity $\left(v_i^{t+1}\right)$ and position $\left(x_i^{t+1}\right)$ of particle i at iteration $(t+1)$ are calculated using the following canonical equations [24]:

$$v_i^{t+1} = a.v_i^t + b.rand_1.\left(P_{\text{best},i} - x_i^t\right) + c.rand_2.\left(G_{\text{best}} - x_i^t\right) \quad (1)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

The velocity update equation is composed of three distinct terms: (1) Inertia term $\left(a.v_i^t\right)$: the first term that represents the particles's momentum, influencing its tendency to continue moving in its current direction; (2) Cognitive term $\left(b.rand_1.\left(P_{\text{best},i} - x_i^t\right)\right)$: the second term that models the particle's memory and motivation to return to its own best-know position, b: the cognitive acceleration coefficient, $rand_1$: a uniformly distributed random number in $[0, 1]$; and (3) Social term $\left(c.rand_2.\left(G_{\text{best}} - x_i^t\right)\right)$: the third term which models the swarm's collective influence, directing the particle toward the global best position, c: the social acceleration coefficient, $rand_2$: a random number in $[0, 1]$.

The particle's new position is then determined by simply adding the newly calculated velocity to its current position. This iterative process is repeated until a predefined termination criterion is met. The final G_{best} solution represents the globally optimal or near-optimal solution identified by the algorithm within the expansive search space. The algorithm's inherent simplicity, minimal parameter count, and rapid convergence make it a computaionally efficient and highly effective tool for tackling complex non-linear optimization problems [24].

This paper comparatively evaluates the independent performance of economic versus technical optimization objectives to establish prioritization criteria for multi-objective formulations. PSO is employed for its computational efficiency and ability to deliver acceptable optimal solutions suitbale for the intended comparative analysis.

2.2. Objective functions

2.2.1. Objective function for minimizing system generation cost

The generation cost minimization objective function for a power system, defined across all generating units and the slack bus, is expressed as follows [25]:

$$\min G(c) = \min \sum_{i=1}^{n_p} \left(x_i + y_i . P_{g.i} + z_i . P_{g.i}^2 \right) \tag{3}$$

Where $G(c)$ represents the function of system generation cost, [US$/h]; x_i, y_i, z_i denotes the cost coefficients of the i^{th} generator, including operational, fuel consumption, and loss-related costs, respectively; $P_{g,i}$ expressed the output active power of the i^{th} generator; and n_p is the total amount of generator, solar generation, and slack bus in system [MW]. Table 1 shows the values of these parameters.

Table 1. *System values and fuel cost coefficients using for simulation*.

Generator number	**Parameter of Fuel cost coefficient**			$P_{\min}$	$P_{\max}$	$Q_{\min}$	$Q_{\max}$
	x_i	y_i	z_i				
	[$/h]	[$/MWh]	[$/MW^{2}h]	[MW]	[MW]	[MVAr]	[MVAr]
Generator 1	0	2.00	0.00375	50	200	-20	200
Generator 2	0	1.75	0.01750	20	80	-20	100
Generator 5	0	1.00	0.06250	15	50	-15	80
Generator 8	0	3.25	0.00834	10	35	-15	60
Generator 11	0	3.00	0.02500	10	30	-10	50
Generator 13	0	3.00	0.02500	12	40	-15	60

The optimization of the objective function is subject to several crucial constraints, including: (1) Power balance (generation equals consumption plus losses); (2) Limits on the active power output of each generating unit; (3) Limits on the reactive power output of each generating unit; and (4) Bus voltage magnitude limits. These constraints are mathematically expressed as follows.

$$\sum_{i=1}^{n_p} P_{g.i} = P_{\text{load}} + \sum_{j=1}^{m} P_{\text{loss},j} \tag{4}$$

$$P_{g,i_{\min}} \leq P_{g,i} \leq P_{g,i_{\max}} \tag{5}$$

$$Q_{g,i_{\min}} \leq Q_{g,i} \leq Q_{g,i_{\max}} \tag{6}$$

$$V_{g,i_{\min}} \leq V_i \leq V_{g,i_{\max}} \tag{7}$$

Where P_{load} is the total consumption demand of the system, [MW]; $P_{\text{loss},j}$ denotes the active power loss of the j^{th} branch, with $j = 1, \dots, m$, [MW]; $P_{g,i_{\min}}$, $P_{g,i_{\max}}$ are the minimum and maximum active power limit of the i^{th} power plant, [MW]; $Q_{g,i_{\min}}$, $Q_{g,i_{\max}}$ represent the minimum and maximum reactive power limit of the i^{th} power plant, [MVAr]; and $V_{g,i_{\min}}$, $V_{g,i_{\max}}$ are the voltage limits of buses, [V], $i = 1, \dots, n_p$.

2.2.2. Objective function for minimizing system power losses

To achieve optimal generator operation, it is essential to model the system's power loss while strictly constraining generator active power. The aggregate power loss at all nodes is given by:

$$P_{\text{loss}} + jQ_{\text{loss}} = \sum_{i=1}^{n} V_i I_i^* = V_{\text{bus}}^T I_{\text{bus}}^* \quad (8)$$

$$I_{\text{bus}} = Y_{\text{bus}} V_{\text{bus}} \quad (9)$$

$$V_{\text{bus}} = Y_{\text{bus}}^{-1} I_{\text{bus}} \quad (10)$$

Where P_{loss}, Q_{loss} are active and reactive power loss of the system; V_{bus} is the column vector of the node voltages; I_{bus} is is the column vector of the current into the node; Y_{bus} is an admittance matrix. Minimizing active power losses is an important objective in the operation of transmission systems, as these losses directly affect energy losses and energy costs. Power losses can be determined through the following methods:

$$\min(P_{\text{loss}}) = \min(\sum_{i=1}^{n} 3.I_{line\_i}^2 . R_{line\_i}) \quad (11)$$

Active power loss can also be determined from the difference between total generated power and total required load power:

$$\min(P_{\text{loss}}) = \min(\sum_{i=1}^{n_p} P_{g,i} - \sum_{k=1}^{n_p} P_{\text{load}}) \quad (12)$$

Where P_{loss} is the power loss on the line; $I_{\text{line\_i}}, R_{\text{line\_i}}$ are the current and resistance of the i^{th} transmission line; $P_{g,i}$ P_{load} are the active power of the i^{th} generator and the total load power.

For this objective function, constraints are the same to the formula (5), (6), and (7).

To strictly enforce system constraints, an exterior penalty method is employed. Violations of the power balance (Eq. 4) and inequality constraints (Eqs. 5-7) are addressed by incorporating quadratic penalty terms into the objective function, as formulated in Eq. 13. This approach transforms the constrained optimization into an unconstrained formulation, eliminating the need for specialized repair operators while ensuring feasibility at convergence [26].

$$F_{\text{penalized}} = F + K\sum(\Delta P_{\text{balance}})^2 + K\sum \max(0, g_j)^2 \quad (13)$$

Where $K = 10^6$ indicates the large positive penalty factor and g_j is the inequality violations.

2.3. Application of PSO to the specific OPF problem

2.3.1. Step-by-step application of PSO

The step-by-step procedure is now described as follows: Step 1 – Initialization: Generate random population of particles (position = control variables, velocity = 0); Step 2 – Evaluation: Compute objective function (Eq.3 and/or Eq.8) and penalty term for constraint violations; Step 3 – Update personal best (P_{best}) and global best (G_{best}); Step 4 – Update velocity and position using Equation (1) and (2); Step 5 – Repeat until maximum iterations (1000) or reaching convergence.

2.3.2. Bounds of control and state variables

Upper and lower bounds of control and state variables are adopted from standard IEEE 30-bus system which are consistent with [27] and shown in Table 2.

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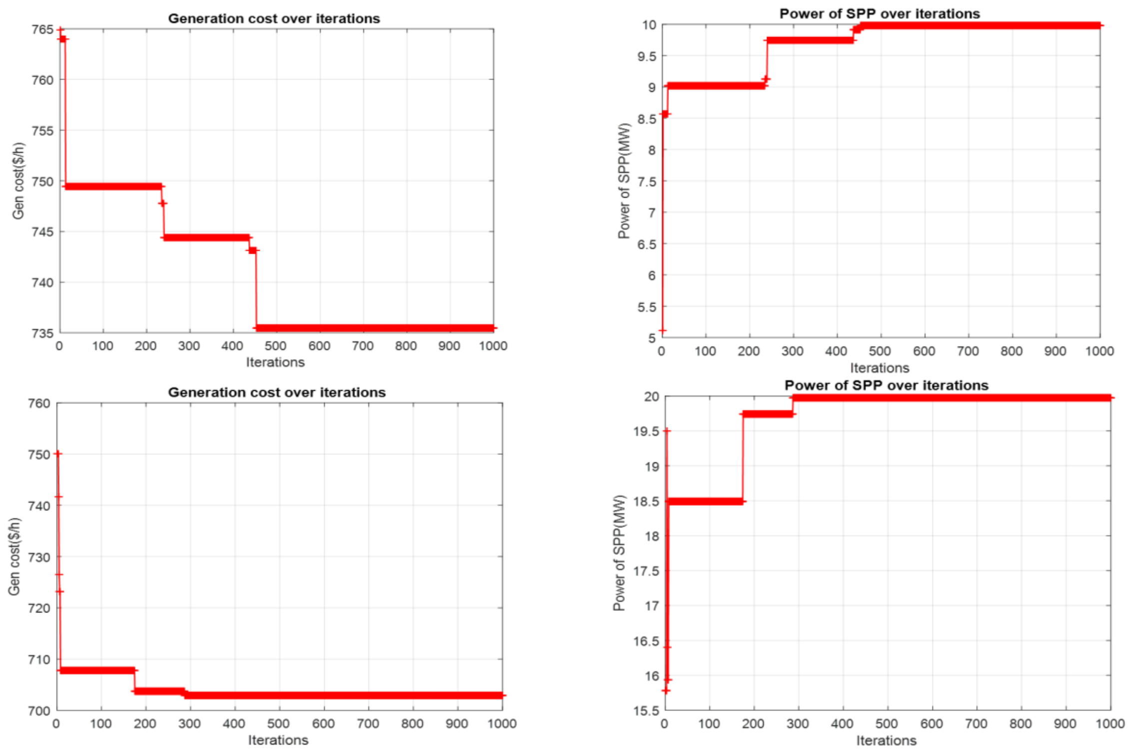
Table 2. *Upper and lower bounds of control and state variables.*

Variable	Location	Lower bound	Upper bound	Unit
Generator active power ($P_{g,i}$)	Bus 1	0	360.2	MW
	Bus 2	0	140.0	MW
	Bus 5, 8, 11, 13	0	100.0	MW
Generator reactive power ($Q_{g,i}$)	Bus 1	-40	50	MVAr
	Bus 2, 5	-40	40	MVAr
	Bus 8	-10	40	MVAr
	Bus 11, 13	-6	24	MVAr
Bus voltage magnitude (V_i)	All bus	0.95	1.10	p.u.
Transformer tap ratio (T_k)	Branches 4-12, 6-9, 6-10, 28-27	0.90	1.10	p.u.

3. Results and Discussion

The simulations in this research were conducted on the modified IEEE 30-bus transmission system, with parameters adopted from [27]. This system features 6 generators and 41 transmission lines, having a total active and reactive power load of 189.2 MW and 107.2 MVAr, respectively. Referencing previous work by [28], which applied Biogeograph-Based Optimization (BBO), the safe PV penetration limit is defined between 0 MW and 60 MW to avoid violations of system security constraints. Accordingly, and assuming 400 W/panel capacity, this study considers PV penetration level as a key constraint in the generation cost optimization objective function. We analyze four distinct research cases, where the PV penetration capacity incrementally increases by a factor of 10. These cases correspond to overall penetration levels of 5.3%, 10.6%, 15.9%, and 21.2% of the total load, respectively.

3.1. Determine the optimal penetration of PV generation into the transmission grid using PSO



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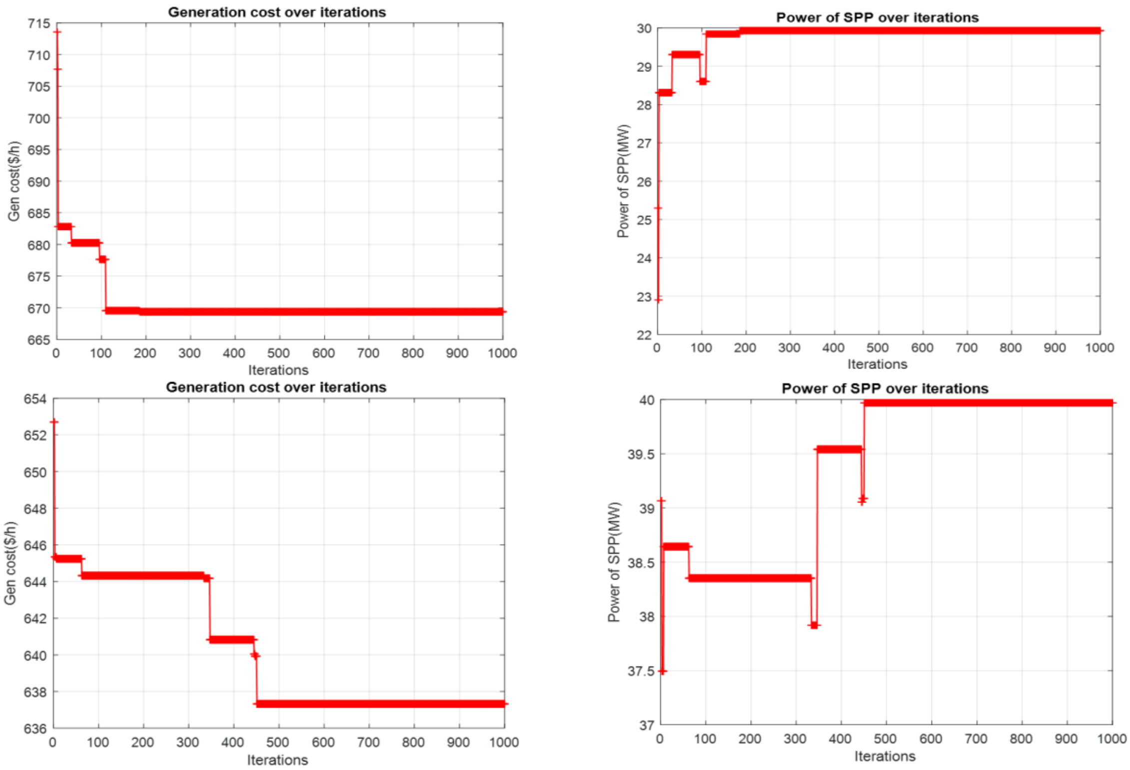

Figure 1. *Solar power plant power limit check results using PSO algorithm.*

Building upon the system configuration detailed in the methodology, the results for Problem 1 – Determining the optimal PV penetration level that minimizes total generation cost – are presented in the following description.

Table 3. *Case studies and Problem 1's simulation results.*

Case study	Installed Capacity	Optimal Cost	Optimal PV Penetration	Penetration Level	Loop
	[MW]	[$/h]	[MW]	[%]	
Case 1	10	735,468	9,980	5.3	443
Case 2	20	703,026	19,973	10.6	179
Case 3	30	668,723	29,930	15.9	103
Case 4	40	637,131	39,969	21.2	448

The PSO algorithm, executed over 1000 iterations in MATLAB, was applied to Problem 1, the results demonstrate a clear inverse correlation between PV integration capacity and system generation cost, as summarized in Table 3.

The highest generation costs across the four cases consistently occurred in the initial loops (e.g., 765,250 US$/h in Loop 2 of Case 1, and 765,187 US$/h in Loop 3 of Case 2), underscoring the PSO's convergence efficacy (see Figure 1). The preliminary findings confirm two key points: (1) PV integration significantly reduces total system generation cost; and (2) Cost reduction benefits increase as PV penetration approaches the technical capacity constraint (i.e., the optimal PV output closely aligns with the installed capacity). However, these results treat the PV source only as a seventh centralized generator rather than a traditional six-generator-30-node power transmission grid. The crucial impact of the PV source's location on both generation cost and system operational efficiency remains unaddressed, thus motivating the formulation of Problem 2.

3.2. Optimal PV source's placement for cost minimization

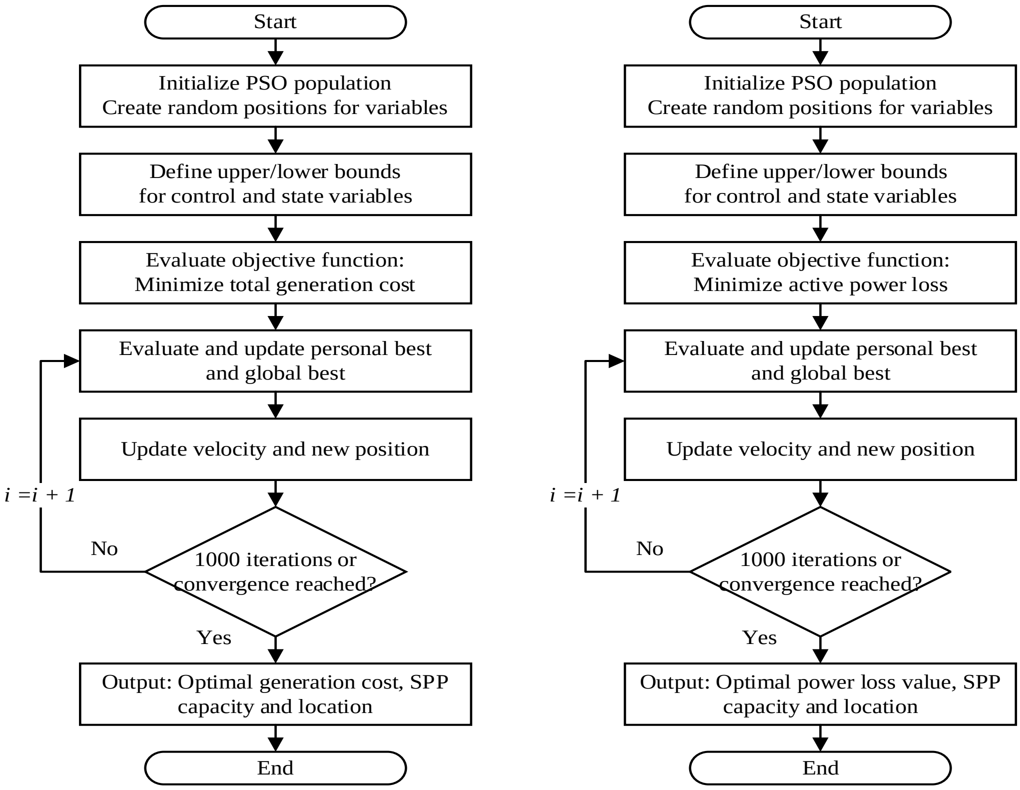

Figure 2. *Flowchart of simulation execution with objective functions*
(a) Generation cost objective function (b) Power loss objective function.

The flowchart of simulation is shown in Figure 2. Problem 2 investigated the impact of PV source placement on system economics, fixing the capacity to a single unit and iteratively simulating its placement across all nodes (from Node 2 onwards) using the PowerWorld platform. The simulation, run across the four penetration cases established in Problem 1, yielded the following results (see Table 4) for the optimal installation bus that minimizes total generation cost:

Table 4. *Case studies and Problem 2's simulation results.*

Case study	Installed Capacity [MW]	Optimal Node	Minimum Cost [$/h]
Case 1	10	30	764,074
Case 2	20	5	728,269
Case 3	30	5	693,727
Case 4	40	5	659,568

The simulation network is shown in Figure 3. For Case 1 (10 MW of PV installed capacity), the optimal placement is Node 30 (the farthest bus), delivering the best cost reduction by supplying capacity at a point with significant voltage drop. However, for higher penetration cases (≥ 20 MW), the optimal location shifts and stabilizes at Node 5 (see Figure 4). This is notable, as Node 5 serves as a key intermediate bus, receiving power from Node 2 and supplying the longest branch of the network. Placing the PV source here reduces power flow and required generation from the upstream source (Node 2) to Node 5. This strategy yields substantial cost reductions, especially when displacing expensive thermal generation, and also provides environmental benefits by reducing fossil fuel consumption and associated greenhouse gas emissions. These outcomes make three key assertions regarding PV placement: (1) PV integration generally reduces system generation cost, though the reduction rate varies by location; (2) Optimal cost reduction is site-specific, indicating that not all grid locations are equally suitable for PV optimization; and (3) Cost reduction is non-linear with respect to increased PV installed capacity.

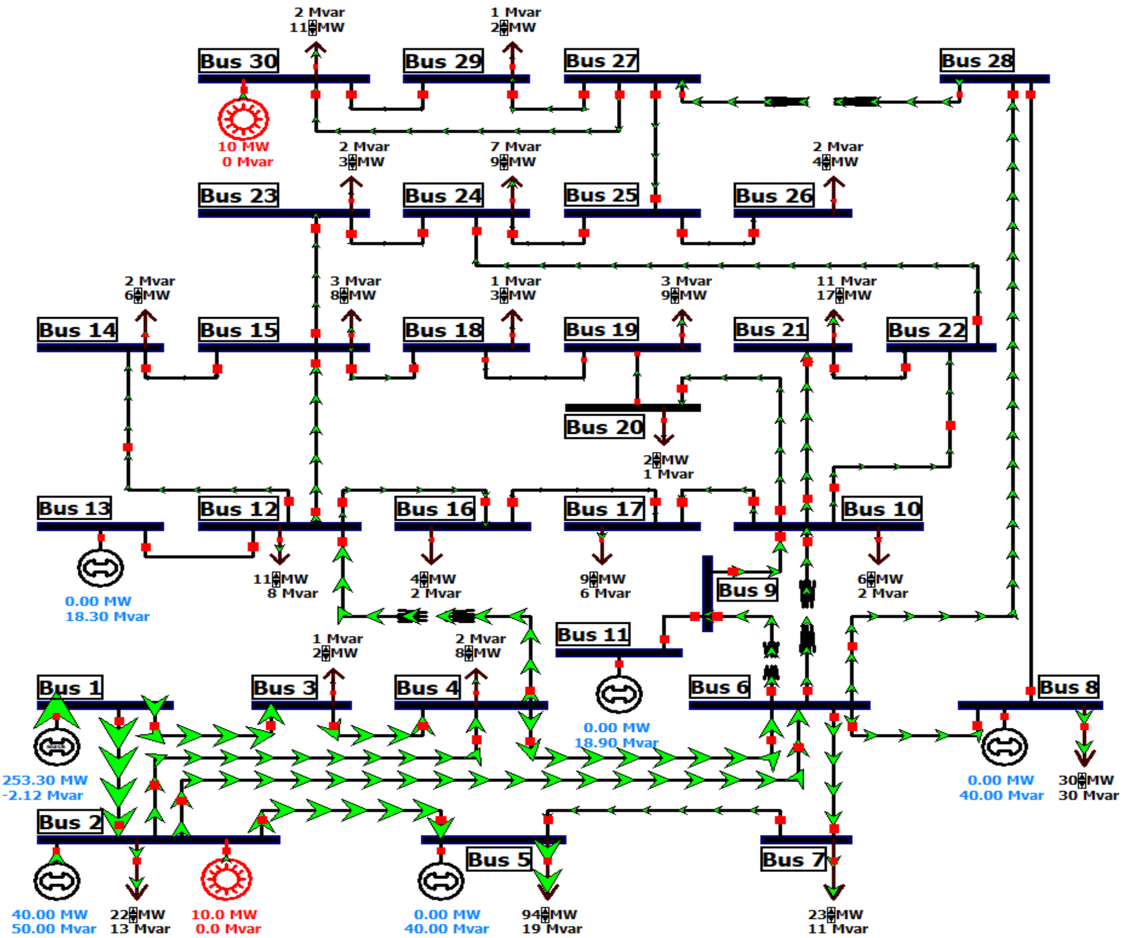

Figure 3. *Simulation with IEEE-30bus sample transmission network.*

3.3. Optimal PV generation for power loss minimization

Analysis of power loss across all cases, as depicted in Figure 4 and Table 5, confirms that system losses generally decrease with increasing SPP capacity. Nevertheless, the non-uniform reduction, particularly the less pronounced loss minimization observed at Node 26, highlights that maximizing capacity does not guarantee an equivalent reduction in losses across all buses. This underscores the imperative for optimization of both location and capacity to effectively minimize system power losses.

Finally, Table 6 confirms that all optimal placement scenarios maintain strict adherence to system security constraints. The lowest and highest bus voltage magnitudes across all simulation cases (0.9915 pu to 1.0820 pu) remain well within the permissible operational range. This verification ensures that the proposed SPP placements and capacity levels successfully optimize the dual objectives without

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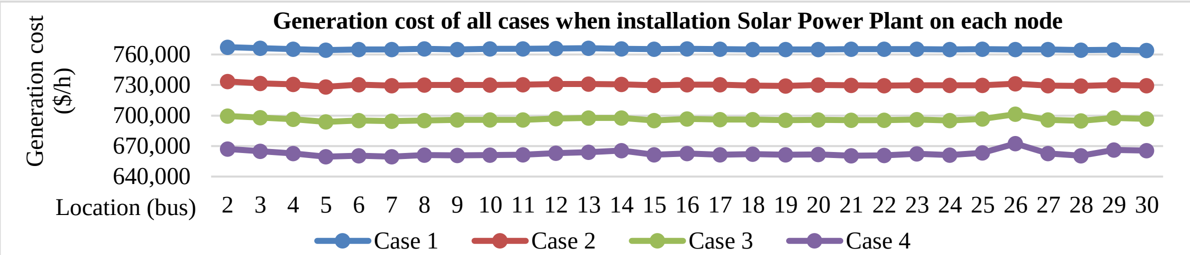
compromising system stability or power quality standards.



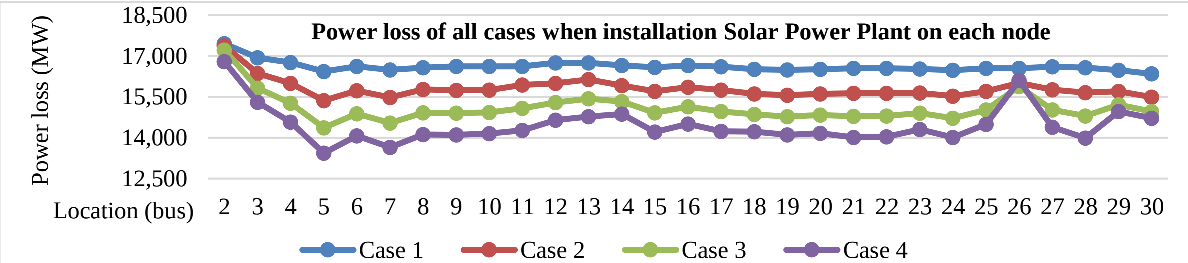


Figure 4. *Simulation results with objective functions.*

Table 5. *Results before and after installation of SPP with the objective functions.*

Cases of installing SPP with different powers	Lowest of generation cost			Lowest of power loss		
	Location (bus)	Cost ($/h)	Value (%)	Location (bus)	Power (MW)	Value (%)
Objective function of generation cost						
No SPP installation		800.727	0.000		17.552	0.000
Case 1: Power of SPP is 10MW	30	764.074	4.577	30	16.344	6.882
Case 2: Power of SPP is 20MW	5	728.269	9.049	5	15.366	12.454
Case 3: Power of SPP is 30MW	5	693.727	13.363	5	14.368	18.140
Case 4: Power of SPP is 40MW	5	659.568	17.629	5	13.435	23.456
Objective function of power loss						
No SPP installation		866.733	0.000		9.592	0.000
Case 1: Power of SPP is 10MW	30	827.026	4.581	30	8.931	6.891
Case 2: Power of SPP is 20MW	5	783.918	9.555	5	8.482	11.572
Case 3: Power of SPP is 30MW	5	742.043	14.386	5	7.918	17.452
Case 4: Power of SPP is 40MW	5	701.512	19.063	5	7.494	21.872

Table 6. *Lowest and highest voltage values of optimal locations in cases of SPP installation.*

Voltage of objective functions	Case 1		Case 2		Case 3		Case 4	
	Voltage (p.u.)	Location (bus)	Voltage (p.u.)	Location (bus)	Voltage (p.u.)	Location (bus)	Voltage (p.u.)	Location (bus)
Objective function of generation cost								

Highest	1.0820	11	1.0820	11	1.0820	11	1.0820	11
Lowest	1.0047	7	0.9927	30	0.9927	30	0.9927	30
Objective function of power loss								
Highest	1.0820	11	1.0820	11	1.0820	11	1.0820	11
Lowest	1.0031	7	0.9915	30	0.9915	30	0.9920	30

3.4. Economic comparison between objective functions

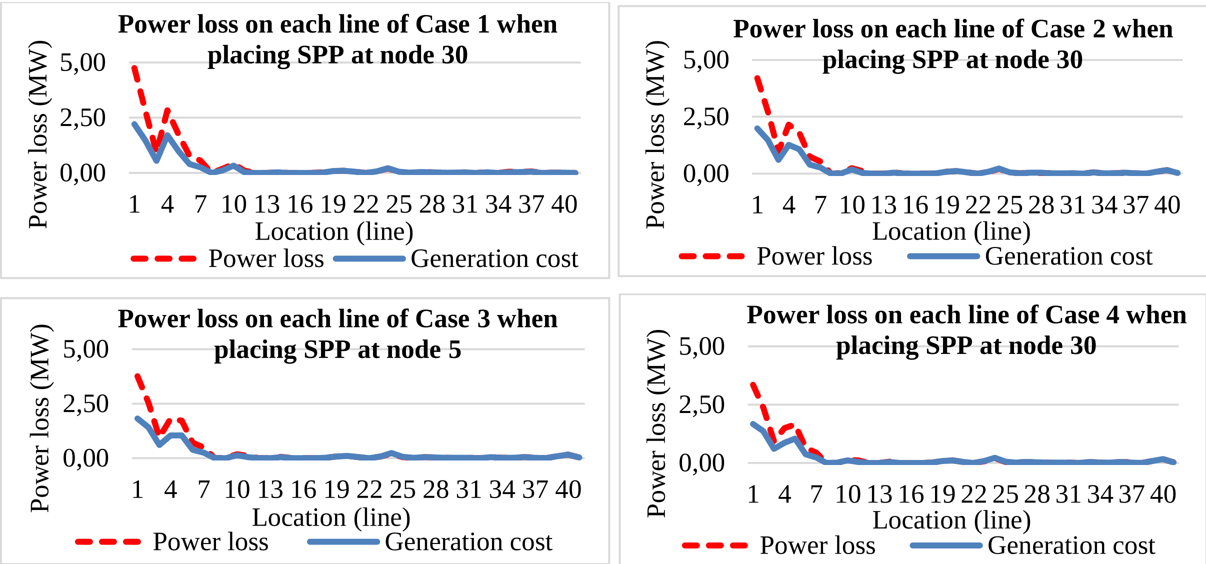


Figure 5. *Power loss on each line with different objective functions for each case.*

Table 7. *Mean cost when simulations with objective functions.*

	Location (bus)	P_{load} (MW)	P_{loss} (MW)	P_{total} (MW)	$P_{totalGen}$ (MW)	P_{SPP} (MW)	C_{total} ($/h)	C_{mean} ($/MW/h)
Objective function of generation cost								
None		283.4	17.552	300.948	300.948	0.0	800.739	2.733
Case1	30	283.4	16.344	299.422	289.422	10.0	764.051	2.706
Case2	5	283.4	15.366	298.089	278.089	20.0	728.252	2.680
Case3	5	283.4	14.368	296.833	266.833	30.0	693.699	2.655
Case4	5	283.4	13.435	295.690	255.690	40.0	659.541	2.629
Objective function of power loss								
None		283.4	9.592	292.986	292.986	0.0	866.733	2.880
Case1	30	283.4	8.931	292.347	282.340	10.0	827.026	2.858
Case2	5	283.4	8.482	291.725	271.720	20.0	783.918	2.819
Case3	5	283.4	7.918	291.266	261.280	30.0	742.043	2.781
Case4	5	283.4	7.494	290.898	250.890	40.0	701.512	2.744

The simulation results in Figure 5 indicate a notable finding: the power loss on individual lines, when optimized for generation cost, is consistently lower than when optimized directly for power loss across all cases. This outcome demonstrates that although the primary goal of the cost optimization is economic, it concurrently yields superior technical performance in reducing power losses within the grid. This highlights a critical correlation between the two objective functions and their positive impact on overall power performance.

Analysis of Table 7 confirms that the generation cost is sensitive to variations in both the power output and the location of the installed SPPs. Furthermore, the selection of the objective fucntion significantly influences the mean generation cost. Specifically, in Case 4, the average cost when simulating the power loss objective is 2,744 US$/MWh, which drops substantially to 2,629 US$/MWh when simulating the generation cost objective. This 4.191% difference underscores the substantial impact the choice of objective function has on economic outcomes in optimization scenarios.

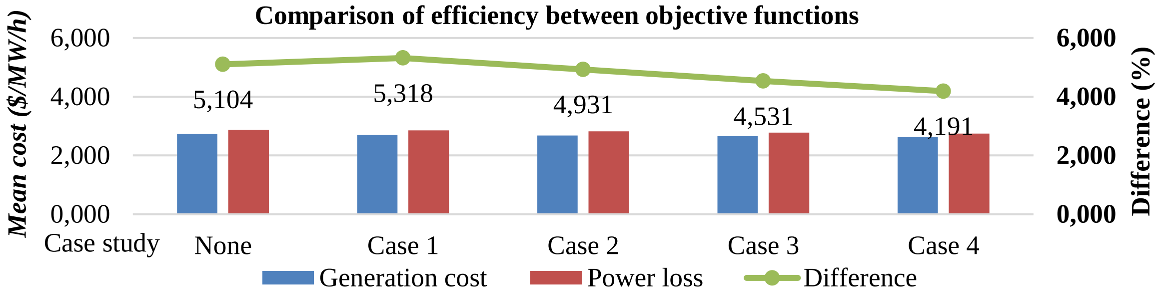


Figure 6. *Comparison of efficiency between objective functions.*

As shown in Figure 6, the mean generation cost under the cost-optimization objective is consistently lower than under the loss-minimization objective. The gap between them narrows as SPP capacity increases. Across all four cases, the generation cost objective proves more robust, improving economic performance while also reducing grid losses. This is confirmed by an average cost difference of 4%–6%, reinforcing its superiority for both economic and technical outcomes.

In general, a comparative analysis of SPP integration focused on minimizing generation cost versus minimizing power loss reveals a surprising synergy: the strategy prioritizing the economic objective is superior for both. The main finding is that the generation cost minimization approach consistently yields a Pareto-superior outcome. This means it successfully achieves the lowest total operating cost and the lowest amount of system losses simultaneously, thereby out-performing the strategy aimed solely at loss reduction. This seemingly counterintuitive results is rooted in the fundamental economics of power dispatch. The cost-optimization algorithm must inherently internalize the cost of losses as lost energy still needs to be generated and paid for, even though it is not sold. Consequently, the algorithm is compelled to identify dispatch solutions that not only utilize the cheapest available generation sources but also strategically minimize long-distance power flows, which are the primary cause of high losses. Essentially, the most economical operational schedule inherently becomes the most physically efficient one. In contrast, an optimization strategy focused purely on reducing losses is cost-blind, It mind commit an expensive local generator simply to achieve a marginal reduction in losses. While technically effective, this approach results in an economically inefficient state for the overall power system.

3.5. Real-World Application of the Optimization Model in Grid Planning and Operation

Our optimization model for Solar Power Plant (SPP) location and capacity is not only relevant in academic studies but also offers direct applicability to real-world grid planning and operation. The insights gained from this study can help grid planners optimize the integration of solar power into existing transmission systems, leading to reduced system costs and power losses, as well as enhanced grid stability. The model can be integrated into grid planning tools to assist planners in determining the optimal location and capacity of SPPs, accounting for system constraints such as voltage limits and power flow capacities. In real-time operation, the optimization model can dynamically adjust the dispatch of solar generation based on real-time demand and renewable energy availability, ensuring that the grid operates efficiently and cost-effectively. Furthermore, the model can be extended to incorporate energy storage systems (such as Battery Energy Storage Systems – BESS), helping to address the variability of solar generation and improving the flexibility and resilience of the grid. In summary, the model provides a powerful framework for smart grid development by helping to balance the dual objectives of minimizing generation costs and reducing power losses. The findings from this study, particularly the synergy between cost-effective and loss-minimizing strategies, underscore the potential for solar power to play a central role in sustainable and resilient power system designs.

4. Conclusions

The integration of SPP into the transmission grid presents a complex, multi-objective optimization problem demanding comprehensive considerations of economic efficiency, technical security, and operational suitability. This study specifically addressed this challenge by developing a framework aimed at simultaneously minimizing total system power losses and optimizing overall power generation costs. The PSO algorithm was systematically employed to solve sequential sub-problems: determining the optimal installed SPP capacity for minimum generation cost, and identifying the optimal SPP installation location for both minimum generation cost and minimum power loss. All simulations were rigorously performed on a modified IEEE 30-bus test system using the MATLAB and PowerWorld software environments. The single-objective simulation and comparative analyses yielded several significant conclusions regarding optimal RE integration: (1) Strategic placement and sizing of SPP significantly enhance overall system efficiency, reaffirming that maximizing benefits requires more than simply increasing capacity; (2) The economic and technical benefits are non-linear. It means that increasing SPP capacity does not result in a proportional reduction in costs or losses; (3) The identification of the optimal SPP installation bus is crucial and highly site-specific. It means that not all locations can effectively optimize the system in terms of both costs and losses, reinforcing the necessity of location-aware algorithms; and (4) The strategy of optimizing the SPP location and capacity based on the cost minimization objective proved superior to the loss minimization objective.

It is conclusively affirmed that the strategy of integrating SPP with the primary goal of minimizing electricity generation cost is the most effective approach. This economic strategy not only achieves the largest reduction in total system cost but also concurrently delivers superior results in reducing system power losses. This efficacy stems from exploiting the locational value and the zero-fuel-cost characteristic of solar power, which naturally guides the system toward the optimal economic and technical operating point. This research confirms a basic tenet for the modern system, particularly for smart-grids: the most economically efficient design is also the most technically robust solution.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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