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Original scientific paper

A Multi-Objective Approach with Modified Particle Swarm Optimization and Hybrid Energy Systems

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Abstract: Designing a photovoltaic (PV) power grid involves intricate considerations, focusing on sizing the PV system and strategically optimizing its placement. Intelligent multi-objective optimization techniques are crucial for addressing the complexity of this task, seeking an optimal solution that balances various objectives such as maximizing energy production, minimizing costs, and ensuring system reliability. In this research, we have selected Modified Particle Swarm Optimization (MPSO) as a suitable multi-objective optimization technique. The primary objective of this optimization is to maximize the energy generated by the PV system, involving the minimization of installation costs, including expenses associated with solar panels, batteries, and related equipment. The optimization technique aims to determine the capacity of the PV system, considering factors such as energy demand, available space, and budget constraints. The ultimate goal is to achieve maximal energy production while adhering to specified budget and space limitations. Optimizing the placement of solar panels is crucial for maximizing energy production. This optimization process takes into account various factors, including shading, panel orientation, tilt angle, and spacing between panels. Utilizing optimization algorithms, the aim is to identify the most effective configuration that ensures the highest energy production. The final step involves implementing the selected PV system design, considering practical installation considerations and regulatory requirements. This comprehensive approach ensures that the designed PV power grid not only meets energy production goals but also considers real-world constraints and compliance with relevant regulations. Through the use of a Hybrid Energy System (HES) with a 15 kW PV scheme and a modest bank, maximum investments for the user and a reduction in carbon influence of more than half can be achieved. This outcome was observed across all four sites evaluated in this research, involving two building types.

Keywords: energy production optimization; hybrid energy system (HES); modified particle swarm optimization (MPSO); multi-objective optimization; photovoltaic power grid

1 INTRODUCTION

The task of sizing photovoltaic (PV) power grids and optimizing their placement through multi-objective intelligent optimization techniques represents a crucial and multifaceted endeavor intersecting renewable energy systems and advanced computational methods [1]. In our world grappling with the challenges of climate change and an increasing demand for sustainable energy sources, photovoltaic (PV) systems have emerged as a promising solution [2]. These systems harness sunlight to generate electricity, making them integral to the global transition toward clean and renewable energy sources [2].

Efficiently designing and deploying PV systems is paramount to maximize their energy generation potential and economic viability. This involves determining the optimal sizing of PV arrays and their placement within a given geographical area, considering multiple objectives [3]. Objectives may include maximizing energy production, minimizing installation costs, enhancing grid reliability, and reducing greenhouse gas emissions.

To address the complexity of this task, researchers and engineers have turned to intelligent optimization techniques, leveraging computational algorithms and artificial intelligence to explore the vast design space of PV systems [4]. Multi-objective optimization allows the simultaneous balancing of conflicting goals, arriving at solutions representing the best compromise. In this context, the "sizing of photovoltaic power grids and optimal placement by multi-objective using intelligent optimization techniques" is an innovative field seeking to revolutionize how we design, install, and manage PV systems [5-7]. By integrating advanced optimization methods with solar technology, it promises more efficient, sustainable, and cost-effective solutions critical to our global transition to clean energy. This approach holds significant promise for addressing pressing challenges and ensuring a more sustainable and environmentally friendly energy future [8].

Steps for Optimizing PV Systems:

1. Identify specific objectives for the PV system, such as maximizing energy generation, minimizing costs, or improving system reliability, guiding the optimization process.
2. Gather relevant data about the installation site, including solar radiation levels, climate conditions, energy demand, available space, and budget constraints.
3. Select suitable multi-objective optimization techniques capable of handling the complexity of the problem (common techniques [9]).
4. Determine the PV system's capacity (number and size of solar panels) considering energy demand, available space, and budget constraints, aiming to maximize energy production within specified limits.
5. Optimize solar panel placement to maximize energy production, considering factors like shading, panel orientation, tilt angle, and spacing between panels, using optimization algorithms to find the best configuration.
6. Use the optimization algorithm to explore trade-offs between different objectives, generating a set of solutions known as the Pareto front, where each solution represents a different trade-off.
7. Analyze the Pareto front to select the most suitable key based on the project's goals and priorities (e.g., minimizing costs while meeting energy production and reliability requirements).
8. Validate the design through simulation and modeling to ensure it meets performance and reliability criteria, making adjustments if necessary.
9. Implement the selected PV system design, considering practical installation considerations and regulatory requirements.
10. Continuously monitor the PV system's performance and conduct regular maintenance to ensure efficient operation over its lifespan.

The paper is organized as follows: Section 2 provides a literature survey, Section 3 outlines the proposed methodology, Section 4 details the experimental analysis, and the last section presents the conclusion.

2 LITERATURE SURVEY

To ensure the security of the essential buses within the system and progress toward complete visibility, Pal et al. (2014) devised a strategy. Buses with high voltage, extensive connectivity, and robust communication facilities are prioritized, along with considering the transient and dynamic stability of the entire system. To enable monitoring of the power network in both normal operation and controlled islanding, [11] presented a PMUs placement model based on the Integer Linear Programming (ILP) approach. We explore various implementations of the bus effect and redundant measurement.

Addressing the Optimal Power Flow (OPF) issue, [12] introduced two variants of Chemical Reaction Optimization (CRO): conventional CRO and a Simplified version of CRO (SCRO). SCRO, based on canonical CRO, allows energy return from the buffer and focuses solely on wall-ineffective collision implementation. Implementing SCRO not only simplifies the process but also enhances its effectiveness in resolving the OPP. When considering the zero injection bus effect, both canonical CRO and SCRO are tested for complete network observability.

The Maximum Loadability Limit (MLL) method for calculating the system's steady-state voltage stability is a time- and effort-saving approach [13]. Load margin, voltage stability, and security margin can all be calculated if MLL is known. The FVSI value closest to unity represents the maximum loadability at the bifurcation point. Extreme load and FVSI are determined at the point of instability. The maximum capacity of each load bus is graded from the lowest to the greatest based on its smallest value. The branch with the highest FVSI value is deemed the most crucial, while the bus with the highest rank represents the weakest bus.

In a study conducted by [14], MATLAB was utilized to analyze various components of the Single-Phase Solar Photovoltaic Rooftop System. The overall results are promising, indicating that solar photovoltaic systems can now be deployed in various locations across India and the world. Conversely, performance evaluation in terms of material science is imposed by the infrastructure.

[15] emphasized the significance of developing an improved methodology for managing reactive power in grid-integrated solar photovoltaic systems with maximum power point conditions. Altering the reference reactive power supplied to the grid and comparing it with the injected reactive power obtained from the proposed methodology are the two steps taken to assess the effectiveness of the proposed method.

In the realm of photovoltaic (PV) applications, solar PV water pumping systems are utilized to meet the demand for water in irrigation, livestock watering, and village water supply, among other applications. [16-18] demonstrated that the design of a solar PV water pumping system could be optimized. They proposed, investigated, and executed their work on the novel optimum operating point tracker of a photovoltaic (PV) system using an adaptive variable step-size Perturb and Observe (P&O) Maximum Power Point Tracking (MPPT) strategy.

The study may lack validation using real-world case studies or applications, which are essential for demonstrating the practical applicability and effectiveness of the proposed approach in diverse contexts and operating conditions. Conducting case studies and field validations could enhance the credibility and relevance of the optimization methodology.

3 PROPOSED HYBRID ENERGY SYSTEM

3.1 Photovoltaic System

A photovoltaic (PV) system consists of an inverter and an array of PV panels. There are primarily three varieties of PV panels: monocrystalline, polycrystalline, and thin-film. Due to their combination of low cost and high efficiency, polycrystalline panels are often considered the most cost-effective choice. In this investigation, our PV system is modeled using a multi-crystalline module, as depicted in Fig. 1.

The PV system employed in this study was modeled using Pvlib in the Python programming environment. Pvlib allows for the generation of a highly accurate model of the system using user-defined parameters. The DC parameters were calculated using the De Soto PV array model, and the PV cell temperature was estimated. The incidence angle of the PV panels was modified with specified values for refractive index, glazing extinction coefficient, and glazing thickness.

To determine the solar position, the date, longitude, and system installation site were used in conjunction with the technique provided in [reference]. The Ineichen/Perez model was then utilized to calculate the direct horizontal irradiance, direct normal irradiance, and clear sky global horizontal irradiance.The study considered how much diffused irradiance from the sky would fall on the surface of an inclined PV panel using a model developed by Hay and Davies. It is important to note that the study did not account for spectral losses.

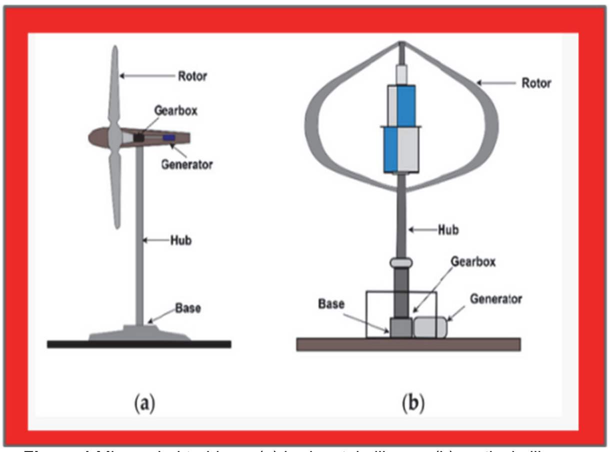

Figure 1 Minor wind turbines: (a) horizontal alliance, (b) vertical alliance

The coefficients for the PV modules were taken from a database maintained by the California Energy Commission (CEC) and accessible through the system advisor model (SAM). From the Tab. 1 CEC inverter database, we also pulled the performance models for grid-connected inverters.

Table 1 PV scheme parameters

Serial Number	Parameter Name	Value / degree
1	Surface tilt angle	18
2	Surface azimuth angle	178
3	Presentation degradation	0.64 %/year

3.2 Modified Particle Swarm Optimization (MPSO)

Modified Particle Swarm Optimization (MPSO) is an optimization algorithm that is derived from the classical PSO algorithm. PSO is a nature-inspired optimization technique based on the social behavior of birds or fish. In PSO, a population of particles explores a search space to find the optimal solution to an optimization problem. MPSO introduces certain modifications or enhancements to the traditional PSO algorithm to improve its convergence speed, solution quality, or applicability to specific problem domains.

Here is a basic explanation of how MPSO works and some of the common modifications:

Particle Representation: Like in traditional PSO, each particle in MPSO represents a potential solution to the optimization problem. Each particle has a position in the search space and a corresponding velocity.

Initialization: The technique starts by seeding a population of particles anywhere in the search space with random beginning values. The location and speed of each particle are produced at random.

Objective Function Evaluation: The fitness or objective function value is calculated for each particle based on its position in the search space. This function represents the optimization problem's goal, and the algorithm tries to minimize or maximize it.

Modifications:

Inertia Weight: MPSO often uses a dynamic inertia weight that changes over time. This weight affects the particle's velocity and controls the balance among exploration and exploitation.

Local and Global Best: Particles update their positions based on their position (local best) and the best-known position among all particles in the population (global best).

Constriction Coefficients: The constriction factor is introduced to help stabilize and control the particle's velocity. It prevents particles from overshooting the optimum and can lead to faster convergence.

Adaptive Neighborhoods: MPSO may use adaptive neighborhood structures to influence particle interactions. Particles can have different numbers of neighbors or dynamically change their neighbors during the optimization process.

Incorporation of Problem-Specific Knowledge: Depending on the problem domain, MPSO can integrate problem-specific knowledge or heuristics to improve search efficiency.

Constraint Handling: Modified versions of PSO can handle constraint optimization problems by incorporating mechanisms to ensure that particles remain within the feasible region of the search space.

Update Rules: In each iteration, particles update their positions and velocities based on the local best, global best, and potentially other factors like inertia weight. These updates aim to guide particles toward better solutions in the search space.

Termination: The algorithm continues for a predefined sum of criterion is met, such as reaching a certain level of convergence or a maximum computational budget.

Solution Retrieval: The best-found solution, often associated with the global best particle, represents the optimal solution to the optimization problem.

MPSO is a versatile optimization technique, and the specific modifications applied depend on the problem being solved and the goals of the optimization. These modifications can help fine-tune the algorithm's behavior to make it more efficient and effective in finding solutions to various types of optimization problems.

3.3 MPSO can be Used for Sizing of Photovoltaic Power Grid

Modified Particle Swarm Optimization (MPSO) is an optimization algorithm that can be used to size a photovoltaic (PV) power grid. Sizing a PV power grid involves determining the optimal configuration of PV panels, inverters, and other components to meet a specific energy demand or maximize energy production. MPSO can help in finding the optimal sizing by adjusting various parameters of the PV system to meet your objectives, which could include minimizing costs, maximizing energy production, or achieving a specific level of reliability.

Here's how MPSO can be applied to the sizing of a photovoltaic power grid:

Define the Objective Function: The first step is to define an objective function that represents your optimization goal. For PV system sizing, common objectives include maximizing energy production, minimizing the levelized cost of electricity (LCOE), or achieving a specific payback period. The objective function should consider factors like panel capacity, inverter size, battery storage, location, and other relevant parameters.

Parameterize the Problem: Identify the parameters that can be adjusted in the PV system, such as the number and capacity of PV panels, the size and type of inverters, the size of energy storage (if used), and any other relevant design variables.

Initialize the MPSO Algorithm: Initialize the MPSO algorithm with a population of particles. Each particle characterizes a potential solution, which is a set of parameters for the PV system. The particles' positions and velocities will be updated during the optimization process.

Fitness Evaluation: Calculate the goal function's value using the particle's location parameters to determine the particle's fitness.

Update Particle Positions: Apply the MPSO algorithm to update the sites and velocities of particles based on their fitness. This process involves adjusting the parameters of the PV system to find a better solution iteratively.

Termination Criteria: Define termination criteria for the optimization process, such as aextremesum of iterations, a convergence threshold, or a time limit.

Obtain the Optimal Sizing: Once the optimization process is complete, the algorithm should provide the optimal set of parameters that define the size and configuration of the photovoltaic power grid that meets your predefined objectives.

System Design and Implementation: Use the results from the MPSO optimization to design and implement the photovoltaic power grid according to the recommended sizing. This may involve procuring the required components, installation, and commissioning.

Validation and Monitoring: After the system is operational, regularly monitor its presentation to ensure that it encounters the desired objectives. Changes may be necessary if environmental conditions change or if the energy demand fluctuates.

MPSO can help optimize the sizing of a photovoltaic power grid by efficiently exploring a large parameter space and finding the configuration that best matches your specific goals. However, it is essential to consider real-world factors like weather conditions, shading, and local regulations when implementing the optimized design to ensure the long-term success of the PV system.

Hybrid Energy System: The appropriate size of a grid coupled to a HES scheme is discussed in this research with respect to both financial and ecological issues. This study investigated two types of reference buildings: (a) urban residential buildings (hereafter mentioned to as "Residential") and (b) rural residential buildings (hereafter referred to as "Farm") that are utilised for restricted farm activities other than storage. Heating, domestic hot water production, air training, and other electrical accessories account for the bulk of the energy needs of these two building types. In our analysis, we focus on the configuration depicted in Fig. 2, which includes a wind energy battery bank. Since both types of structures can draw power from the grid, the purchasing and selling of surplus energy is an important consideration. To achieve this goal, the HES system must be constructed without excess capacity, maximising feed-in to the grid while minimising overall grid power consumption.

This research took into account a HES system that included PV wind turbine with specific inverters, as depicted in Fig. 3. In order to control the power output from these two generators and meet the needs of the residential building's load source, a microgrid controller was implemented. The microgrid controller oversaw the accusing and discharging of the battery bank as well as the purchasing and selling of electricity to the central utility grid.

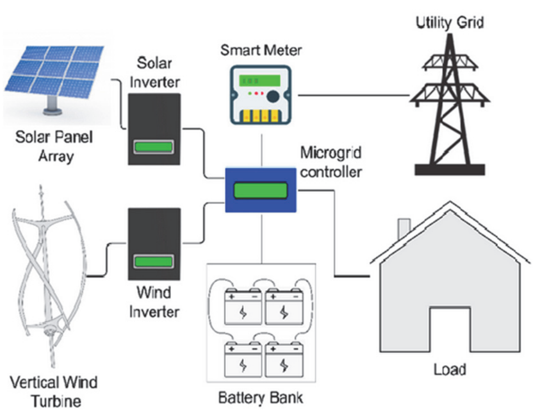

Figure 2 Graphic diagram of the grid-hybrid energy organization

The HES system's economic goals are frequently influenced by local government initiatives. When deciding on the optimal shape and size for the HES system, regional wind and solar factors should also be taken into account. The regional cost of grid-purchased power and the FiT rates for solar and wind energy are highlighted in this case study of southern Taiwan. The Taiwan is a government-owned utility that serves the whole island. Typically, a kilowatt-hour (kWh) costs about $ 0.08. It is worth noting that the FiT tariffs set by the Taiwanese government vary depending on whether the electricity is produced by rooftop solar panels or onshore wind turbines. When determining FiT rates, the installation's footprint is also taken into account. Cost of grid-purchased power is calculated, which must account for variable FiT the net balance of electricity bought from grid (PB) may be determined, one of our economic goals. The net present cost (NPC), often known as the net present value, is another economic goal taken into account here. The HES system's NPC includes the initial investment cost (Ccap), the cost to replace the battery bank (Crep), the cost to operate and maintain the system (Cop), and the cost to salvage the scheme (Cs) after its useful life (T). We see the formula for determining the NPC.

4 EXPERIMENTATION RESULTS

Here, we will regulate the ideal location and number of PV sources for 33-bus and 69-bus distribution systems. The projected system has a 3.72 MW capacity, 2.30 MVAR in total network losses, a 12.66 kW network voltage, 209.913 kW in real network losses, and 142.52 kVAR in reactive losses at a single power factor of 0.85 post- prophase.

Graph showing the relative importance of the various objective functions (counting overall system power losses), shin deviation. Fig. 2 shows (a) the voltage profile under different conditions, (b) the optimisation algorithm for the 33 bus and the unit's output power factor, and (c) the total power losses of the network, including active and reactive losses, under the unit's output factor. The best answer is found by employing the fuzzy decision procedure.

4.1 HES PV Components

In this analysis, 330-watt multi-crystalline PV modules manufactured by Motech Industries were utilised to simulate a solar system. The parameters of this module have somewhat different CEC database values than those listed in the data sheet. Tab. 2 displays the CEC settings we utilised to maintain model consistency with Pvlib/Python. Based on the estimated total system power output, an inverter was selected from the list of possible inverters in Tab. 3. The maximum power output (Psys) of the PV module is used by the PV system model to choose which inverter to use. The inverters may be found in the CEC file. Tab. 2 and Tab. 3 reflect a weighted average of prices found in various sources on the internet.

Table 2 Single diode model limits of the Motech solar panel

Value	Parameters
329.9 W	PSTC
72	Ncell
37.66 V	Vmp
1.966 m	Length
0.992 m	Width
0.3 US$/Wp	Cost

4.2 Sites and Hourly Load Outline

Chosen to characterize the four major climate zones. We chose site in our study. Tab. 2 displays the sites selected from the TMY3 dataset. The load profile is changed for the "Farm" building type by 30% more than "Residential", while the load profile for the "Residential" building type is maintained at the level it was at when the TMY3 dataset was used as a starting point. Fig. 3 displays the hourly load profiles for several "Residential" building sites.

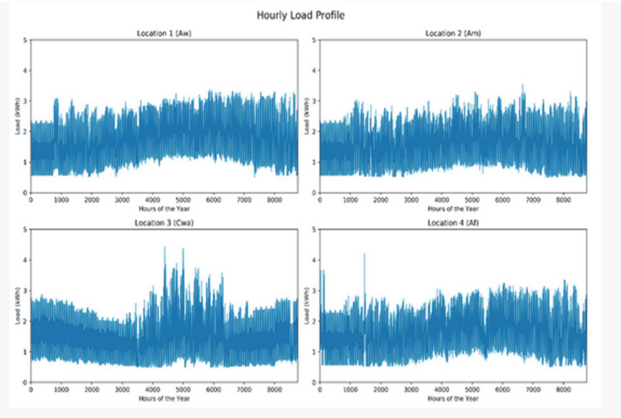

Figure 3 Hourly load profiles for the different sites

For the 33 bus and the unit's output a three-dimensional graph depicting the value of the goal functions has been provided. Fig. 9 displays the voltage profile for a number of different scenarios (b), as well as the overall power losses of the network, with active and reactive losses, with an output factor of 0.85 pre-phase from the unit (c). The optimum action is depicted here in solid blue. The optimised positioning and distribution of PV sources' output power.

Table 3 Inverters used for the PV scheme

Parameters	Psys < 5.3 kW	Psys < 6.6 kW	Psys < 7.6 kW
Prated / W	5300	7600	9780
Vrated / V	240	250	260
Cost / US$	950	1550	2100

5 CONCLUSIONS

In conclusion, the conducted research has yielded valuable insights into the intricate process of designing a photovoltaic (PV) power grid. Emphasizing intelligent multi-objective optimization, particularly utilizing Modified Particle Swarm Optimization (MPSO), has proven pivotal in achieving a balanced and optimal solution for PV system deployment. The primary objective of maximizing energy generation while minimizing installation costs has remained central throughout this research endeavor. Optimizing solar panel placement has emerged as a critical aspect in achieving the overarching goal of maximizing energy production. Considering factors such as shading, panel orientation, tilt angle, and spacing between panels, optimization algorithms have played a crucial role in identifying the most effective configuration for ensuring the highest energy production efficiency. The final step involves the practical implementation of the selected PV system design, taking into account real-world considerations such as installation logistics and adherence to regulatory requirements. This comprehensive approach ensures not only meeting energy production goals but also addressing real-world constraints and ensuring compliance with relevant regulations. The integration of a Hybrid Energy System (HES) featuring a 15 kW PV scheme and a modest energy storage bank has demonstrated significant benefits. Consistent results across all four evaluated sites encompassing two building types reveal that this approach can lead to maximum investments for the user while simultaneously achieving a remarkable reduction in carbon footprint by over half.

In the future, the research establishes a robust framework for the design and implementation of PV power grids, emphasizing the importance of intelligent optimization techniques and a comprehensive, multi-objective approach. The findings contribute not only to the field of renewable energy but also to the broader goal of sustainable and environmentally conscious energy practices. Future research could explore the integration of advanced machine learning techniques, such as deep learning, reinforcement learning, or neural networks, with modified particle swarm optimization (PSO) for hybrid energy system optimization. These techniques could enhance the ability to learn complex patterns, improve decision-making under uncertainty, and adaptively adjust optimization strategies based on real-time data and feedback.

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