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RESEARCH ARTICLE

Stochastic Optimal Energy Planning of the Multi-connected Grids by the Presence of Bi-facial PV Panels: Interaction of Micro-nano and Main Grid

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Abstract

The increasing greenhouse gas (GHG) emissions from fossil fuel-based energy systems have accelerated the global push toward cleaner technologies. Bi-facial photovoltaic (BPV) panels, capable of capturing solar irradiance from both sides, have emerged as a promising solution due to their higher energy yield and comparable costs to traditional PV systems. This paper explores the integration of BPV panels into a multi-connected grid comprising nano-, micro-, and main grid layers. A stochastic optimization framework is developed to address the uncertainties of solar irradiance. The problem is formulated as a Mixed-Integer Linear Programming (MILP) model and solved using the Augmented Epsilon Constraint (AEC) method in the General Algebraic Modeling System (GAMS) environment. Results demonstrate that incorporating BPV panels reduces microgrid operational costs by approximately 20%, boosts nano-grid profits by about 81%, and cuts emissions by about 10%, highlighting their potential to enhance system efficiency, flexibility, and sustainability.

Keywords: bi-facial photovoltaic (BPV), energy management (EM), multi-grids optimization (MGO), renewable energy sources (RES), solar energy.

1 Introduction

1.1 Overall survey on the subject of the study

The past shows that using fossil-fuel-based units to supply electricity can significantly affect the future of our planet for the next generation. Therefore, many efforts have been made toward more sustainable energy resources such as solar, wind, ocean waves, green hydrogen, and other green energy sources. Also, this attention has been significant but has not been enough to rely only on these sustainable resources [1, 2]. Recent advances have been made to improve the performance and efficiency of existing technologies. BPV panels are not a very new technology; however, because of the latest advancements in materials and manufacturing, the performance and productivity of such units have increasingly enhanced [3, 4]. These causes mean that their cost and output power become competitive compared to conventional panels. Due to the vast growth in the use of clean energy in

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the form of nano, micro, and mains grids, utilizing such facilities has caused considerable changes in the energy management and planning of these platforms. A multi-structured platform can be referred to as a combination of small, medium, and large grids. This connection can make the whole network resilient and perfectly supply the consumer's needs [5, 6]. The following studies outline the most notable and recent papers examining these issues, ranging from BPV panels to multi-grids and energy management.

1.2 Recent research on the subject

Researchers have addressed various aspects of this subject, from energy management to the impact of various technologies. Recent advancements in microgrid energy management have emphasized integrating artificial intelligence and optimization techniques to enhance system efficiency, resilience, and sustainability. Various approaches have emerged to address challenges associated with distributed energy resources (DERs), uncertainty in renewable energy generation, and dynamic demand-response scenarios. Yu et al. [7] developed a responsive energy management system (EMS) tailored for hydrogen-powered microgrids, leveraging an improved particle swarm optimization algorithm. Their model incorporates a stochastic framework to manage uncertainties in grid-connected and island modes. This approach notably improves operational reliability while optimizing cost and energy efficiency, particularly through the strategic use of hydrogen fuel cells and thermal energy supply. In another contribution, Kumar et al. [8] proposed a Golden Jackal Optimization (GJO) algorithm for energy scheduling in hybrid microgrid systems equipped with battery storage. The GJO method demonstrates strong computational efficiency and rapid convergence compared to conventional techniques, such as PSO and Artificial Bee Colony. Their simulation results reveal a 96% energy efficiency rate and significant cost reductions, highlighting the practical viability of GJO in energy dispatch scenarios involving photovoltaic, wind, and diesel generation systems. Rashidi et al. [9] addressed the energy management needs of multi-microgrid (MMG) systems using a hybrid model that couples Information Gap Decision Theory (IGDT) with the Tunicate Swarm Algorithm (TSA). Their framework is tailored for tertiary-level control, focusing on minimizing operational costs while ensuring energy supply reliability and infrastructure longevity. The model handles power generation and demand uncertainties by incorporating fatigue life and energy not supplied as key metrics. Simulation through MATLAB and DigSilent confirms its robustness and adaptability under variable conditions. Continuing from prior developments in microgrid control, researchers have also explored environmentally driven strategies and integrated multi-energy systems to align with net-zero goals and sustainability benchmarks. Li et al. [10] introduced an innovative planning strategy for islanded dual-zero microgrids (DZMGs), emphasizing simultaneous net-zero carbon emissions and zero power exchange with the main grid. The proposed model incorporates multi-scale carbon cycle management using components like direct air capture (DAC), solvent storage tanks (SST), and hydrogen storage systems (HSS). Through the optimal sizing of these elements and a dedicated planning model, their system achieved a cost reduction of over 25% compared to existing zero-carbon methods. The work also highlights the influence of carbon pricing and technological maturity on system economics. Ahmad et al. [11] tackled the inherent uncertainty in interconnected electricity-gas energy systems by proposing a two-stage adaptive robust optimization (ARO) framework. This model integrates advanced components such as battery storage, hydrogen conversion systems, and carbon capture technologies. Key to the approach is the robust handling of RES output fluctuations and market volatility through a column-and-constraint generation algorithm. Results on standard IEEE test networks demonstrated zero load shedding and enhanced renewable penetration, reflecting both system resilience and economic efficiency. Zhao et al. [12] developed a robust distributed energy management system for multi-microgrids using a dynamic tube-based model predictive control (DD-TMPC) framework. Their method addresses intraday uncertainties through a dual-timescale MPC decomposition and introduces a game-theory-based trading mechanism. This setup enables real-time adjustments while maintaining system-wide robustness and economic efficiency. Compared to traditional MPC strategies, their DD-TMPC exhibits better adaptability and lower computational complexity, making it suitable for high-variability environments. In addition to the advancements in optimization algorithms and control frameworks, scholars have placed increasing attention on system architecture, cross-vector energy integration, and hierarchical coordination to future-proof energy networks. Vera et al. [13] presented a coordinated planning strategy for electricity-hydrogen integrated energy systems (EHIES), focusing on minimizing lifecycle carbon emissions. Their two-stage model optimizes component sizing and placement (e.g., electrolyzers, hydrogen storage units), taking into account cost, losses, and emissions. Then, using the alternating direction method of multipliers (ADMM), the operational stage assigns emissions responsibility among users and updates cost-emission trade-offs iteratively. Simulation results showed a 3.81% reduction in operational cost and a 15.89% decrease in carbon emissions compared to independently planned systems. Hussain et al. [14] offered a comprehensive review of multi-level EMS, spanning home, aggregator, and grid layers. They analyzed each layer's objectives, constraints, communication technologies, and optimization methods. The authors emphasized the need for hierarchical EMSs to reconcile user-centric goals such as cost savings with grid-level objectives like voltage regulation and reliability. Special attention was given to the impact of electric vehicles and the role of demand response programs in balancing flexibility and stability. Expanding on the evaluation of photovoltaic technologies and their integration into modern energy systems, two recent studies offer valuable insights into the role of bifacial PV modules in both grid-scale optimization and building-level energy coordination. Al-Masri et al. [15] conducted an in-depth comparison between monofacial (MPV) and bifacial (BPV) photovoltaic systems tailored for a utility-scale application in Al-Husainya, Jordan. Using realistic hourly load and climate data, they employed the Marine Predators Optimization Algorithm to determine the optimal number of modules, inverter count, land footprint, and ecological impact for both technologies. Their results showed that BPV systems require 10.5% less installation area and produce more energy while achieving a lower Loss of Power Supply Probability (0.2511% for BPV vs. 0.3534% for MPV). The study validated its results using four additional optimization algorithms and concluded that BPV is a more reliable, economically feasible, and ecologically favorable choice for large-scale deployments in high solar potential regions. Tabar et al. [16] analyzed the impact of BPV panels on the energy planning of interconnected smart buildings. Their framework involved mixed-integer linear programming (MILP) to optimize cost and pollution within a dual-building, multi-source energy network, including CHP units, boilers, wind turbines, and electrical and thermal storage. Through simulations using Energy Plus and Design Builder software, they found that incorporating BPV panels boosted electricity generation by 20% compared to traditional modules. This improvement significantly reduced dependency on external grid imports and led to measurable cost savings, though it had only a minor effect on total emissions. Their findings support the strategic use of BPV in dense urban networks and mixed-use infrastructures.

1.3 The main hypothesis of this paper

The central hypothesis of this study is that integrating BPV panels into a multi-connected grid, encompassing nano-, micro-, and main grid layers, can substantially enhance overall energy efficiency, reduce greenhouse gas emissions, and provide a more flexible and reliable energy management framework. By harnessing the dual-sided irradiance absorption capability of BPV panels, energy systems can achieve higher output with comparable or even reduced system costs relative to traditional monofacial PV technologies. Furthermore, this hypothesis assumes that when BPV integration is supported by a stochastic optimization approach that accounts for the inherent variability of solar irradiance, the planning outcomes will be more resilient and practical for real-world applications. The hypothesis is tested through a detailed MILP-based model implemented in GAMS and solved by the AEC method, aiming to quantify the tangible advantages of BPVs in a layered grid environment.

1.4 Paper's sections organizations

The rest of the paper is organized as follows: the most important renewable-based unit mentioned above, such as BPV panels, is explained in Section 2. Furthermore, the most critical constraints and equations that affect planning are introduced in this section. Section 3 presents the solving approaches and the characteristics and parameters of the multi-structure grid test system. Sections 4 and 5 elaborate on numerical results and a conclusion, respectively.

2 BPV modeling and grid constraints

2.1 BPV panels

As renewable energy technologies continue to advance, the drive toward cleaner and more efficient power solutions has given rise to innovations like BPV panels. These solar panels represent a significant leap forward from traditional models. Unlike standard PV panels that absorb sunlight only from their front surface, BPV is designed to generate electricity from both sides (as illustrated in Figure 1). This dual-sided

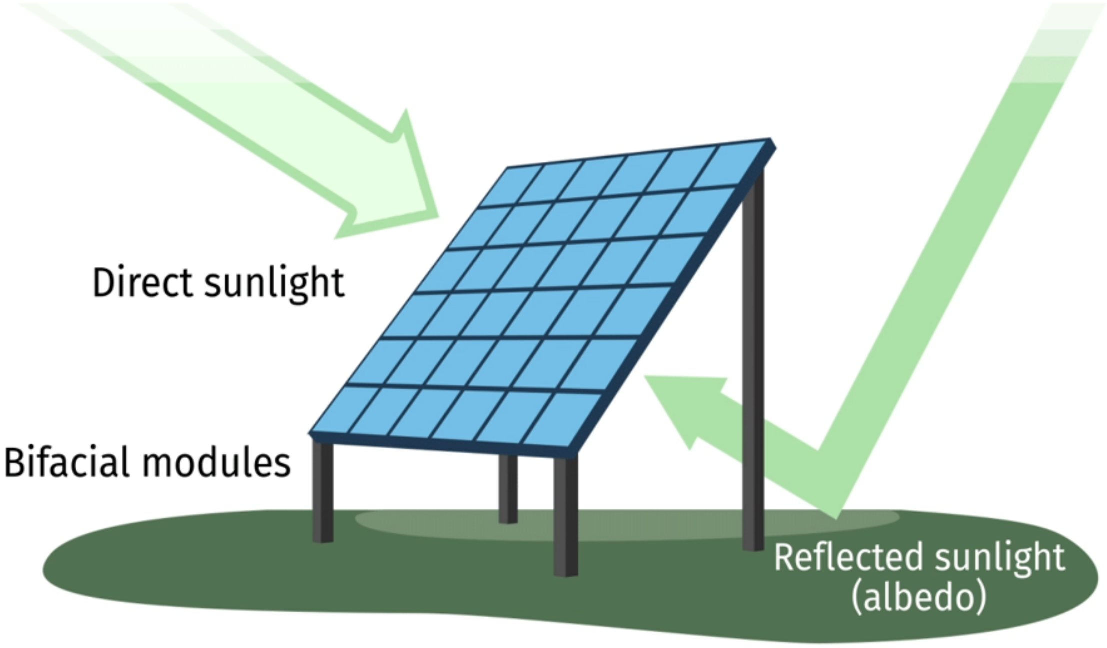

Figure 1. The overall schematic of the practical BPV panels [17].

configuration allows it not only to capture direct solar radiation from above but also to benefit from light reflected off surrounding surfaces, enhancing total energy output. The temperature behavior of the solar cells is characterized through Eq. (1), while Eqs. (2) and (3) are used to determine the power generation capacity of both conventional and BPV systems [16].

For other unit information and characteristics, refer to Appendix 1 at the end of the paper.

$$T_j(t) = T_{amp} + \frac{G_T(t)}{G_{Isrc}} \times (NOCT - 20) \tag{1}$$

$$P_{pY}(t) = \Big(P_{pY,src} \times \frac{G_T(t)}{G_{Isrc}} \times \big(1 - \gamma \times (T_j(t) - T_{jstc})\big) \times N_{pY_s} \times N_{pY_p}\Big) \tag{2}$$

$$P_{BPY}(t) = P_{pY}(t) + \big(C \times P_{pY}(t)\big) \tag{3}$$

Based on the below formulation, $T_j(t)$ is the PV's cell temperature (°C); Temp refers to ambient temperature (°C). $G_T(t)$ is solar radiation on the tilted module plane of PV at time t $(\mathrm{kW/m^2})$, and G_{Isrc} is solar radiation in STC (standard test conditions) $(\mathrm{kW/m^2})$. NOCT is the normal operating cell temperature (°C), P_{pv} is the output power of PV panels (kW), γ is the coefficient related to the power temperature, P_{spv} is the BPV's output power (kW), and finally, C is the factor related to the increment of BPV compared to PV panels. Figure 1 depicts the overall schematic and operation of BPV panels.

It is worth noting that portable energy resources are also considered in this paper; their details are in the Appendix section. The components of the nano-grid, such as thermal and electrical storage units, wind turbines, and portable PV and BPV panels, follow the same mathematical structure used in the microgrid as expressed in the Appendix. The only variations lie in a few parameters, such as capacity and output power. As a result, the detailed equations are not reiterated here.

2.2 The most notable constraints and objective functions

Depending on the planner's goals, a range of objective functions and constraints must be considered. This section outlines the key objectives and the most relevant constraints.

$$\begin{aligned} F_m(\mathbb{S}/\text{Day}) = {} & C_{WT} + \big[C_{PV} \text{ or } C_{BPV}\big] + C_{Bqv}^{m\,\text{main}\,t} \\ & - C_{Sell}^{m\,\text{main}\,t} + C_{Bqv}^{m\,n\,t} - C_{Sell}^{m\,n\,t} + C_{ES}^{m\,m\,t} \\ & + C_{TS}^{m\,m\,t} + C_M + C_{Boiler} + C_{CHP}^{m} \end{aligned} \tag{4}$$

$$\begin{aligned} F_n(\mathbb{S}/\text{Day}) = {} & C_{WT}^{P} + \big[C_{PV}^{P} + C_{BPV}^{P}\big] + C_{Bqv}^{m\,\text{main}\,t} - \\ & C_{Sell}^{m\,\text{main}\,t} + C_{Bqv}^{m\,m\,t} - C_{Sell}^{m\,m\,t} + \\ & C_{ES}^{m\,m\,t} + C_{TS}^{m\,m\,t} + C_{CHP}^{m} \end{aligned} \tag{5}$$

$$\text{Em\_Tm(Kg/Day)} = \sum_{i=1}^{T} (\text{Em}_{MT} + \text{Em}_{CHP}^{m} + \text{Em}_{Boiler} + \text{Em}_{main}^{m}) \tag{6}$$

$$\text{Em\_Tn(Kg/Day)} = \sum_{i=1}^{T} (\text{Em}_{main}^{n} + \text{Em}_{CHP}^{n}) \tag{7}$$

$$\text{Em\_T(Kg/Day)} = \sum_{i=1}^{T} (\text{Em}_{MT} + \text{Em}_{CHP}^{m} + \text{Em}_{Boiler} + \text{Em}_{main}^{m} + \text{Em}_{main}^{n} + \text{Em}_{CHP}^{n}) \tag{8}$$

According to the above, Eqs. (4) and (5) exhibit the proposed multi-structure grid's overall cost, specifically for microgrid and naogrid, which consists of the total cost of various generation and storage units such as CHP, Boiler, micro-turbine, PV, BPV, wind turbine, and other elements. Environmental pollution, which shows itself in the form of Eqs. (6) - (8); demonstrate the total emission of the microgrid's, nanogrid's, and main grid's various pollutant units. All these objective functions must be minimized simultaneously. Along with these objectives are numerous restrictions and constraints; some of the most important ones are mentioned in the following. Related to the electrical and thermal demands, Eqs. (9) – (12) explain the necessity of equality in the generation and demand side of the total power of microgrid and nanogrid, respectively.

$$E_{ld}^{m}(t) = P_{WT}(t) + P_{pY}(t) + P_{MT}^{m}(t) + P_{CHP}^{m} - P_{E,ch}^{m}(t) + P_{E,dch}^{m} + P_{Buy}^{main}(t) - P_{Sell}^{main}(t) + P_{Buy}^{m\_n}(t) - P_{sell}^{m\_n}(t) \tag{9}$$

$$T_{ld}^{m}(t) = P_{Boiler}(t) + TF_{CHP} \cdot P_{CHP}^{m} - P_{T,ch}^{m}(t) + P_{T,dch}^{m} \tag{10}$$

$$E_{ld}^{n}(t) = P_{WT}^{P}(t) + P_{PV}^{P}(t) + P_{CHP}^{n} - P_{E,ch}^{n}(t) + P_{E,dch}^{n} + P_{Buy}^{n\_main}(t) - P_{Sell}^{n\_main}(t) + P_{Buy}^{n\_m}(t) - P_{sell}^{n\_m}(t) \tag{11}$$

$$T_{ld}^{n}(t) = TF_{CHP}\, P_{CHP}^{n} - P_{T,ch}^{n}(t) + P_{T,dch}^{n} \tag{12}$$

3 Modeling approach and practical system characteristics

3.1 Solving method and optimizing manner

As mentioned in the previous sections, the nano-grids and microgrids are integrated into the main grid, forming a layered, interconnected energy system. At this point, the problem is formulated as a three-objective optimization model, aiming to minimize the microgrid's operational cost and maximize the nanogrid's profit while reducing the entire network's overall environmental emissions. The AEC method has been used to achieve accurate and flexible optimization results. The AEC method generates a diverse set of Pareto-optimal solutions by optimizing one objective while treating the remaining constraints with controllable bounds. The "augmented" aspect includes a minor penalization term in the objective function, which enhances the spread and avoids weak Pareto points. This method provides a broad view of trade-offs among objectives, allowing planners to explore various operating scenarios [18, 19].

3.2 Practical Implementation and Run-Time Performance

The proposed MILP model is implemented and executed in GAMS (Win32 version 24.7.3) on a personal laptop with the following specifications: Intel(R) Pentium(R) Silver N5000 CPU 1.10GHz, 8 GB RAM, running Windows 11 Enterprise (64-bit). Despite the modest hardware, the system successfully managed the stochastic optimization problem, solving a filtered set of 50 representative scenarios (selected from an initial pool of 50,000). This result indicates that the proposed framework is computationally practical, even on low-end consumer hardware, making it accessible for educational, research, and small-scale planning purposes. However, more powerful hardware or parallel computing environments would be recommended for real-time or large-scale deployments to reduce computation time further. Compared to existing methods in the literature that rely on swarm intelligence algorithms or real-time predictive control, our approach prioritizes solution robustness and multi-objective flexibility over speed, which may better suit applications requiring high reliability in uncertain environments.

3.3 Proposed multi-grid test system details

The envisioned multi-grid, specifically microgrid setup, integrates a mix of energy sources, including a

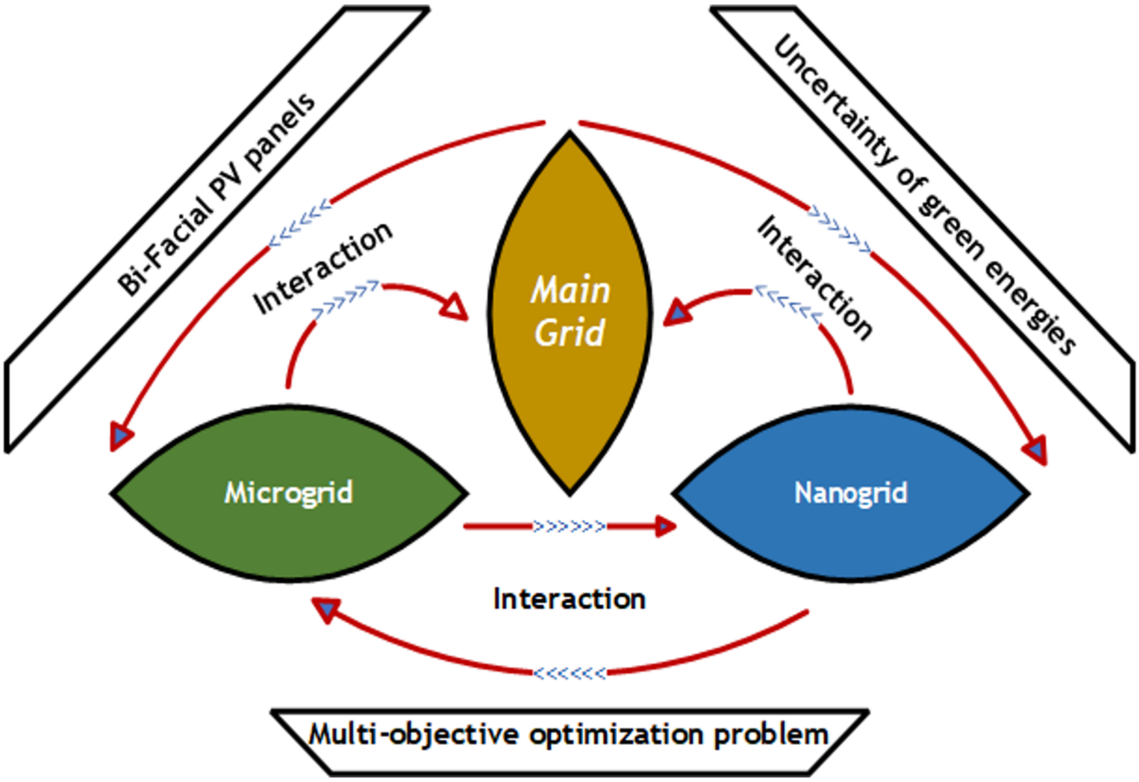

Figure 2. The general overview of the assumed multi-grid network.

wind turbine, solar panels, BPV panels, a combined heat and power (CHP) unit, a boiler, a microturbine, and storage systems for both electricity and heat. Meanwhile, the nano-grid component features a compact wind turbine, portable solar panels, portable BPV panels, a CHP system, and electrical and thermal storage units. This multi-grid framework connects the microgrid, nano-grid, and the main power grid (see Figure 2) in a cohesive network. Energy scheduling is mapped out over 24 hours, divided into six 4-hour blocks. To account for uncertainties, a stochastic approach is used, factoring in variables like wind speed, sunlight intensity (for conventional and BPV panels), fuel costs, and both electrical and thermal demands. These uncertain parameters are modeled with a 30% standard deviation from their actual values to generate scenarios. Out of an initial pool of 50,000 scenarios, 50 are chosen to enhance the system's resilience against unexpected variations.

4 Numerical results

4.1 Before and after implementing BPVs

This section elaborates on the nominal scenario in which BPV did not participate in the planning. It also includes the effect of the BPV panels on the various objective functions of the energy management of these multi-structured grids. The exact value of objective functions for the total cost of the microgrid, the total profit of nanogrid, and the overall contamination before implementing BPVs, which have been calculated and obtained at $49.097, $9.105, and 3143.748 kg, respectively. After utilizing BPVs, there have been enhancements in objective functions, in which the amount of the microgrid's total cost, the nano-grid's total profit, and overall emission have reached $39.24, $16.48, and 2830.7 kg, respectively. Furthermore, Figures 3 and 4 depict the total generated power by mono-facial and BPV panels in the microgrid and nanogrid, respectively.

5 Recap and Conclusion

This research explored how incorporating bi-facial photovoltaic (BPV) panels can enhance the energy management of a multi-layered grid system comprising nano-, micro-, and main-grid structures. By using a Mixed-Integer Linear Programming (MILP) model and solving it with the augmented epsilon constraint (AEC) method in General Algebraic Modeling System (GAMS), the study considered real-world uncertainties in solar irradiance through a stochastic approach. The results were promising; integrating BPV panels led to a 20% reduction in total energy costs for the microgrid, a profit increase of about 81% in the nano-grid, and an overall emission

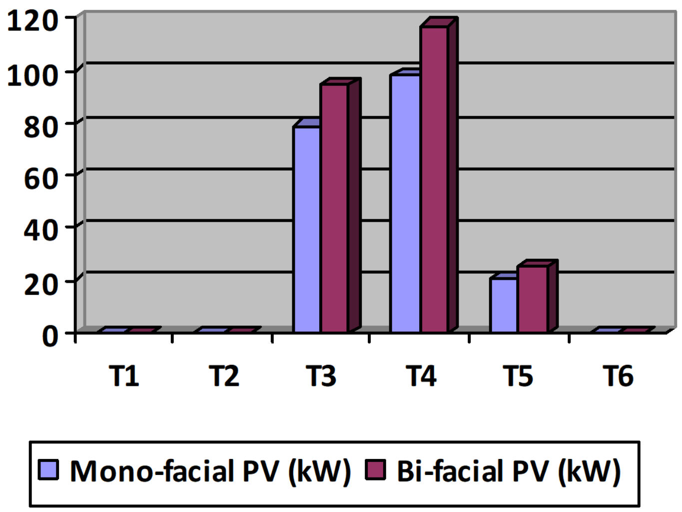

Figure 3. The output power generated by MPV and BPV panels in the microgrid.

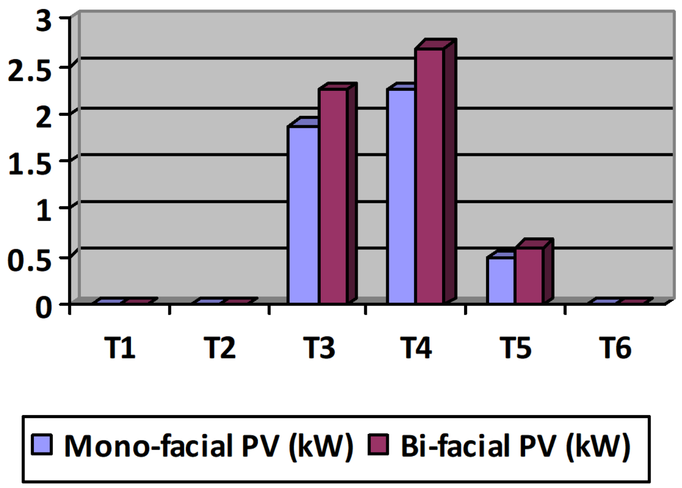

Figure 4. The output power generated by MPV and BPV panels in the nanogrid.

drop of 10%. These outcomes support the idea that BPVs, thanks to their ability to capture sunlight from both sides, can offer more efficient, cost-effective, and environmentally friendly solutions than conventional PVs. This study highlights the meaningful role that modern, dual-sided solar technologies can play in shaping smarter and more sustainable energy systems.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author declares no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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