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Optimization of Photovoltaic System Sizing Using Artificial Intelligence for a 20 KW Hybrid Solar Installation

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Abstract

The growing demand for reliable and cost-effective electricity has accelerated the adoption of solar photovoltaic (PV) systems; however, inappropriate system sizing can lead to excessive installation costs through oversizing or unreliable power supply through undersizing. This study aims to optimize the sizing of a PV power system within the 10–20 kW capacity range using an artificial intelligence-based approach. A detailed PV system model incorporating half-cut monocrystalline PV modules and lithium iron phosphate ($LiFePO_4$) battery storage was developed in MATLAB/Simulink. Solar irradiance and ambient temperature were incorporated to represent realistic operating conditions. Particle Swarm Optimization (PSO), implemented in Python, was used to determine the optimal PV array configuration and battery capacity. System performance was evaluated based on energy output, Loss of Power Supply Probability (LPSP), and Net Present Cost (NPC). The simulations showed that PV output increased with solar irradiance, whereas module efficiency declined as temperature increased. The optimization identified a configuration of 32 PV modules, comprising eight modules in series and four parallel strings, combined with a battery capacity of approximately 690 Ah. This configuration produced a system capacity of approximately 16 kW, achieved an LPSP of 0.006, and

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reduced system cost relative to larger configurations. These findings demonstrate that PSO-based optimization can improve the technical and economic performance of PV system sizing by balancing energy reliability, storage capacity, and system cost. The study provides an integrated optimization framework for designing reliable and cost-efficient PV–battery systems under variable environmental conditions.

Keywords: Artificial Intelligence; Loss of Power Supply Probability; Net Present Cost; Particle Swarm Optimization; Photovoltaic System Sizing

INTRODUCTION

The global energy landscape is currently undergoing a fundamental transition, driven by the dual imperatives of mitigating climate change and ensuring energy security. According to the International Energy Agency (IEA, 2023), the demand for electricity is projected to grow by 3.4% annually through 2026, with the majority of this demand arising from developing economies where grid instability remains a persistent challenge. In this context, Renewable Energy Sources (RES) have migrated from fringe technologies to central pillars of modern power generation. Among these, Solar Photovoltaic (PV) technology has emerged as the most promising solution due to its modularity, minimal maintenance requirements, and the rapid decline in the Levelized Cost of Energy (LCOE), which dropped by approximately 89% between 2010 and 2022 (IRENA, 2023).

However, the integration of solar PV into commercial and institutional applications faces a critical stochastic challenge: the intermittency of solar irradiance (Ibekwe Arinze Ignatius et al, 2026). Unlike conventional synchronous generators, PV output is heavily dependent on diurnal cycles and meteorological conditions such as cloud cover, ambient temperature, and humidity. For a standalone or hybrid system to function reliably, this generation volatility must be buffered by an Energy Storage System (ESS), typically comprised of battery banks (Ibekwe Arinze Ignatius et al, 2025).

The focus of this research is the specific engineering challenge of a 20 kW Hybrid PV System. This capacity represents a critical "middle ground" in power systems engineering often utilized for large residential compounds, rural health clinics, or Small-to-Medium Enterprises (SMEs). In such setups, the system involves a complex interplay between the PV array generation, the battery State of Charge (SoC), the inverter efficiency curve, and the dynamic load profile. Traditionally, sizing defined as the process of determining the optimal capacity of the PV array and battery bank has been performed using deterministic, static methods. Khatib et al. (2013) argue that these static methods are insufficient for hybrid systems because they fail to account for the minute-by-minute fluctuations in power flow. Consequently, there is a growing consensus in academic literature that Artificial Intelligence (AI) and meta-heuristic optimization techniques offer a superior pathway for sizing complex energy systems (Mellit & Kalogirou, 2021).

METHODOLOGY

This study adopted a quantitative simulation-based experimental design to determine the optimal sizing of a 10–20 kW photovoltaic (PV) power system using Artificial Intelligence optimization. The research was implemented using a co-simulation framework combining MATLAB/Simulink and Python. MATLAB/Simulink was used to model the electrical behaviour of the photovoltaic system, while Python was used to implement the Particle Swarm Optimization (PSO) algorithm for determining the optimal PV array configuration and battery capacity.

The optimization process was carried out iteratively. For each candidate system configuration generated by the optimization algorithm, MATLAB simulated the electrical output of the PV array using irradiance and temperature data from Nigerian Meteorological Agency (NiMet). The resulting power output was then evaluated based on system reliability and economic performance indicators.

System Architecture Implemented

The photovoltaic power system developed in this study consists of the following components:

1. Photovoltaic Array
2. DC-DC MPPT Converter
3. Battery Storage System ($LiFePO_4$)
4. DC-AC Inverter
5. Electrical Load

The PV array converts solar irradiance into electrical energy. The DC-DC converter regulates voltage using Maximum Power Point Tracking (MPPT) to ensure the PV array operates at its maximum power point. The battery bank stores excess energy generated during peak solar periods and supplies power when solar generation is insufficient.

Figure 1 below presents the overall architecture of the photovoltaic (PV) power supply system implemented in this study. The system begins with solar irradiance, which serves as the primary energy input captured by the PV array and converted into direct current (DC) electricity. This DC power is regulated by an MPPT (Maximum Power Point Tracking) converter to ensure optimal energy extraction from the solar panels. The regulated power is then stored in the battery bank for energy backup and stability. Finally, the stored DC energy is converted into alternating current (AC) by the inverter, which supplies electrical power to the AC load.

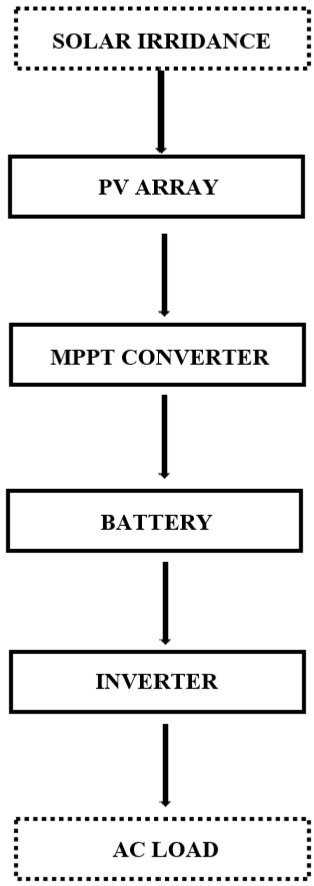

Figure **1**: System Architecture

Power Flow Path of a Standalone Solar Energy Conversion System

These denotes a sequential energy conversion chain: solar energy is generated by the PV array, optimized by MPPT, stabilized through battery storage, converted to AC by the inverter and then delivered to the load

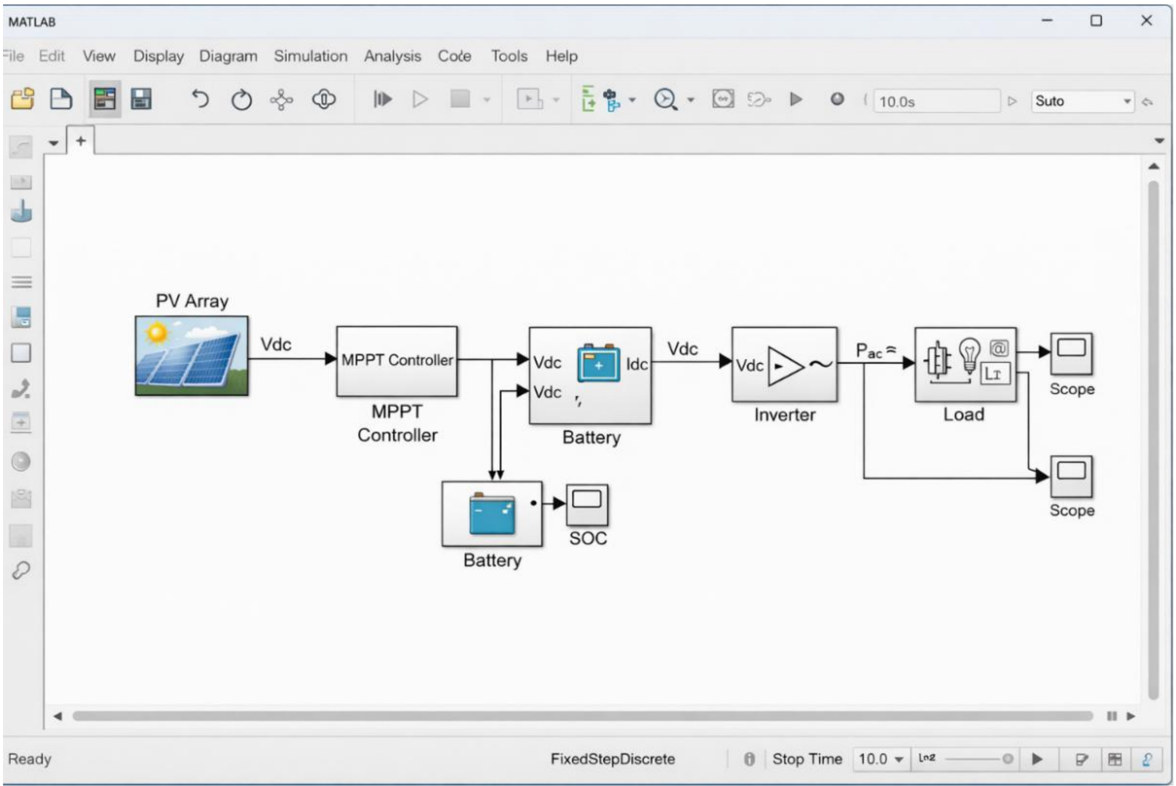

Figure 2: Power Flow Path of a Standalone Solar Energy Conversion System

The diagram represents the power flow path of a standalone solar energy conversion system arranged in a simple Simulink structure:

The PV Array is the primary energy source. It converts solar irradiance into DC electrical power. Its output is not constant because it depends on sunlight and temperature, so the voltage and current from the PV side vary throughout the day.

The MPPT controller comes immediately after the PV array because the PV module must be forced to operate near its maximum power point. In practical terms, this block continuously adjusts the operating point of the solar array so that the system extracts the highest possible power under changing weather conditions. Without MPPT, part of the available solar energy would be lost.

The battery is connected after the MPPT stage to act as the energy storage unit. When PV generation is higher than the demand, excess energy is used to charge the battery. When solar power becomes low or unavailable, the battery discharges and supports the downstream side of the system. In the diagram, the battery therefore serves as the balancing element between variable PV generation and required load demand.

The inverter converts the DC power from the PV-battery side into AC power suitable for conventional electrical loads. Since most residential and laboratory loads operate on AC supply, this block is essential. The inverter also introduces a conversion efficiency, meaning the AC output is slightly lower than the DC input.

The load is the final consumption point of the system. It represents the appliance or group of appliances being powered. In Simulink, this can be modeled as a fixed load, varying load, or time-dependent load profile.

Photovoltaic Module Mathematical Model

The photovoltaic module was modeled using the single-diode equivalent circuit, which accurately represents the nonlinear current-voltage behavior of a solar cell.

Figure 3 below represents the single-diode equivalent circuit model of a photovoltaic (PV) cell. The current source I_{ph} models the photocurrent generated by solar irradiance, while the diode represents the p–n junction behavior of the solar cell. The series resistance R_s accounts for internal conduction losses, and the shunt resistance R_{sh} represents leakage paths within the cell. Together, these components determine the output current and voltage characteristics of the PV module.

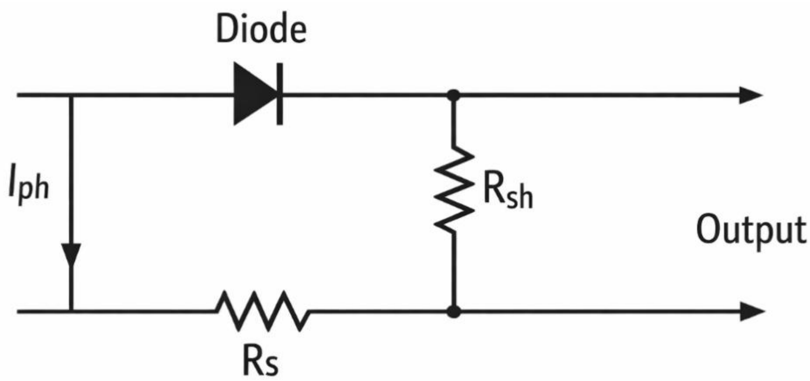

Figure 3: Single Diode PV Model

The output current of the PV cell is given by:

$$I = I_{ph} - I_o \left(e^{\frac{V+IR_S}{nV_t}} - 1\right) - \frac{V + IR_s}{R_{sh}} \quad (1)$$

The photo-generated current depends on solar irradiance:

$$I_{ph} = \left[I_{sc} + K_i(T - T_{ref})\right] \frac{G}{G_{ref}} \quad (2)$$

Photovoltaic Array Configuration

The PV array power is given by:

$$P_{PV} = N_s \times N_P \times P_{module} \quad (3)$$

Where

Ns = Number of modules in series

Np = Number of parallel strings

For the target 20 kW system:

Module rating = **500 W**

$$N_{total} = \frac{20000}{500} = 40\, panels$$

Table 1: Possible configurations tested by the AI algorithm included:

Ns	Np	Total Panels
10	4	40
8	5	40
5	8	40

Each configuration was evaluated during optimization.

Battery Storage Model

The battery bank stores excess energy generated by the PV array.

Battery capacity:

$$C_{bat} = \frac{E_{load} \times D}{V_{bat} \times DoD} \qquad (4)$$

Where

E_{load} = Daily load demand (Wh)

D = Autonomy days

V_{bat} = Battery voltage

DoD = Depth of discharge

The battery State of Charge (SoC) was computed using:

$$SOC_{(t)} = SOC\,(t-1) + \frac{P_{charge} - P_{discharge}}{C_{bat}} \qquad (5)$$

Constraints applied in the model:

$$0.2 \leq SOC \leq 1$$

This ensured the $LiFePO_4$ battery operated within safe limits.

Effect of Solar Irradiance on PV Array Output

The first performance result considered was the variation of array output power with solar irradiance. This result was important because irradiance is the principal environmental driver of PV output.

Table 2: PV Array Output Power at Different Irradiance Levels

Irradiance (W/m²)	Cell Temperature (°C)	Panel Power (W)	Array Power for 40 Panels (kW)
200	36.25	188.75	7.55
400	42.50	377.50	15.10
600	48.75	566.25	22.65
800	55.00	755.00	30.20
1000	61.25	943.75	37.75

Table 2 presents the simulated output power as solar irradiance increased from 200 W/m² to 1000 W/m². The results indicate that array power increased progressively with irradiance despite the accompanying rise in cell temperature.

Figure **4** below shows a near-linear increase in output power as irradiance rises. This confirms the correctness of the implemented PV model, since higher solar input produced greater electrical output. The result also shows that the system retained strong output response even when temperature increased with irradiance, although the power obtained was slightly lower than the ideal theoretical value due to temperature-related de-rating.

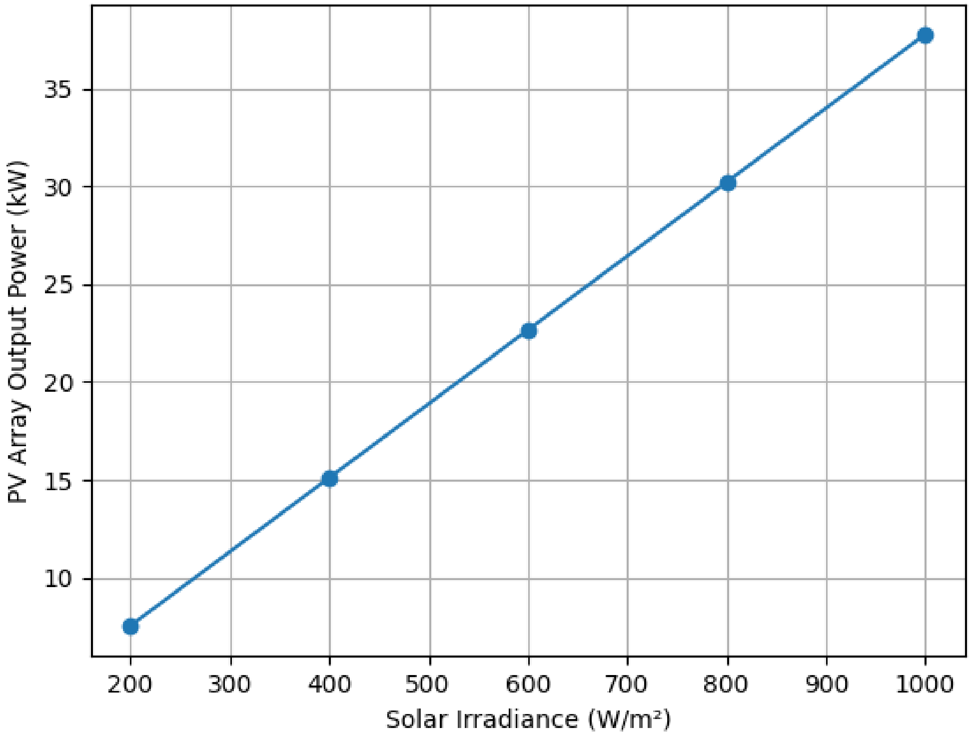

Figure **4**: PV Array Output Power versus Solar Irradiance

Effect of Cell Temperature on Panel Output

The second result considered the influence of temperature on PV power output under constant irradiance. This was necessary because photovoltaic modules are known to lose efficiency as cell temperature rises.

Table 3: Effect of Cell Temperature on Panel Output at Constant Irradiance of 1000 W/m²

Cell Temperature (°C)	Panel Output Power (W)
20	510
25	500
30	490
35	480
40	470
45	460
50	450
55	440
60	430
65	420
70	410

Table 3 shows that panel output reduced steadily as cell temperature increased from 20 °C to 70 °C. This trend reflects the negative temperature coefficient of the selected Half-Cut Monocrystalline module.

Figure 5 below reveals a clear downward slope, showing that temperature rise had a negative effect on module power. This is technically expected because increasing temperature reduces the module voltage more significantly than it increases the current. In practical terms, this result confirms that tropical operating conditions can reduce PV efficiency and therefore must be accounted for during sizing.

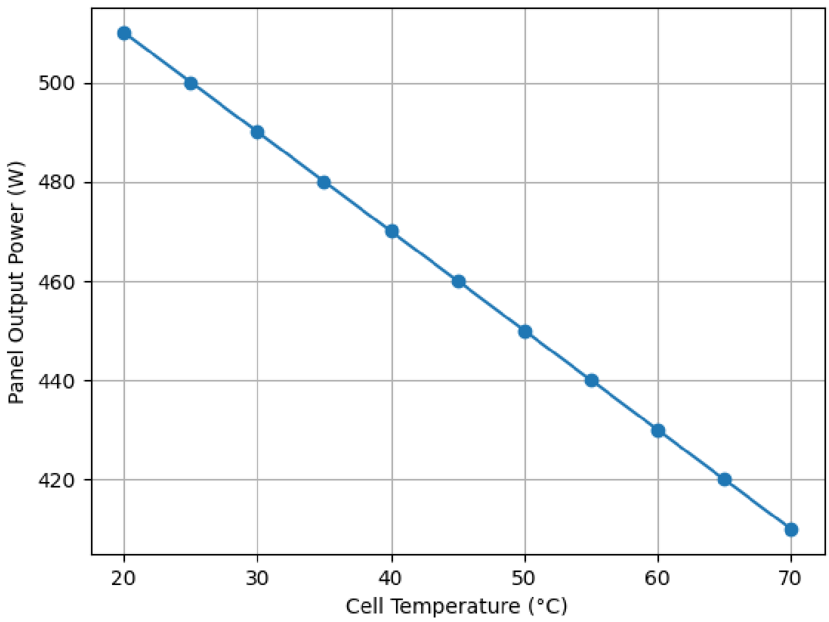

Figure **5**: Effect of Cell Temperature on Panel Output Power

CONCLUSION

This research investigated the optimization of photovoltaic system sizing using Artificial Intelligence for a solar power installation within the 10–20 kW capacity range. The study was motivated by the need to design photovoltaic systems that are both technically reliable and economically efficient, particularly in environments where solar energy serves as a primary electricity source. Traditional sizing approaches often rely on simplified calculations that either oversize the system, thereby increasing installation cost, or undersize the system, resulting in insufficient power supply. In response to this challenge, this research developed a simulation-based optimization framework capable of determining an appropriate balance between system reliability and cost.

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