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AI-Driven Optimization Of Photovoltaic Energy Capture Using Physics-Informed Neural Networks

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Abstract

The global transition to sustainable energy necessitates significant improvements in the efficiency of renewable sources like solar power. Traditional methods for optimizing photovoltaic (PV) panel performance often rely on static positioning or simple sun-tracking, failing to account for complex, real-time environmental variables. This paper explores the application of a Physics-Informed Neural Network (PINN) to dynamically maximize the energy output of a PV system. By integrating the fundamental physical principles of photovoltaics (the single-diode model) with a machine learning framework that processes real-time weather data (irradiance, temperature, cloud cover), the proposed system predicts the optimal tilt and orientation angles for a PV panel. A simulated case study demonstrates that the PINN model increases daily energy capture by approximately 18.5% compared to a fixed-angle system and by 7.2% over a conventional dual-axis tracker, by more intelligently responding to diffuse irradiance and cloud-transition periods. This work underscores the potent synergy between physics-based modeling and artificial intelligence in addressing critical challenges in sustainable energy, a key pillar for societal growth and achieving Sustainable Development Goals (SDGs).

Keywords: Physics-Informed Neural Network, Photovoltaic Optimization, Renewable Energy, Machine Learning, Sustainable Development.

1. Introduction

The quest for clean and sustainable energy is a defining challenge of the 21st century, deeply rooted in the principles of physics and engineering. Photovoltaic (PV) technology, which directly converts sunlight into electricity, is at the forefront of this transition. However, a significant limitation of PV systems is their variable efficiency, heavily dependent on environmental conditions like solar irradiance, ambient temperature, and the angle of incidence of sunlight.

Traditional optimization strategies range from fixed-angle panels, set for a location's average sun path, to active solar trackers that follow the sun's apparent motion. While trackers improve yield, they are mechanical, incur maintenance costs, and often operate on a pre-programmed path, ignoring real-time atmospheric effects like cloud cover that can make diffuse light—which is less dependent on angle—the dominant source.

This paper proposes a novel software-based solution using Physics-Informed Neural Networks (PINNs). PINNs are a class of AI models that embed the governing physical laws (in this case, the electrical characteristics of a PV cell) directly into the learning process [1]. This approach combines the predictive power of data-driven ML with the reliability and generalizability of physical models.

2. Methodology

2.1. The Physical Model: Single-Diode Model of a PV Cell

The electrical behaviour of a PV cell is accurately described by the single-diode model [2]. The governing equation for the current-voltage (I-V) characteristic is:

Formula 1: Single-Diode Model

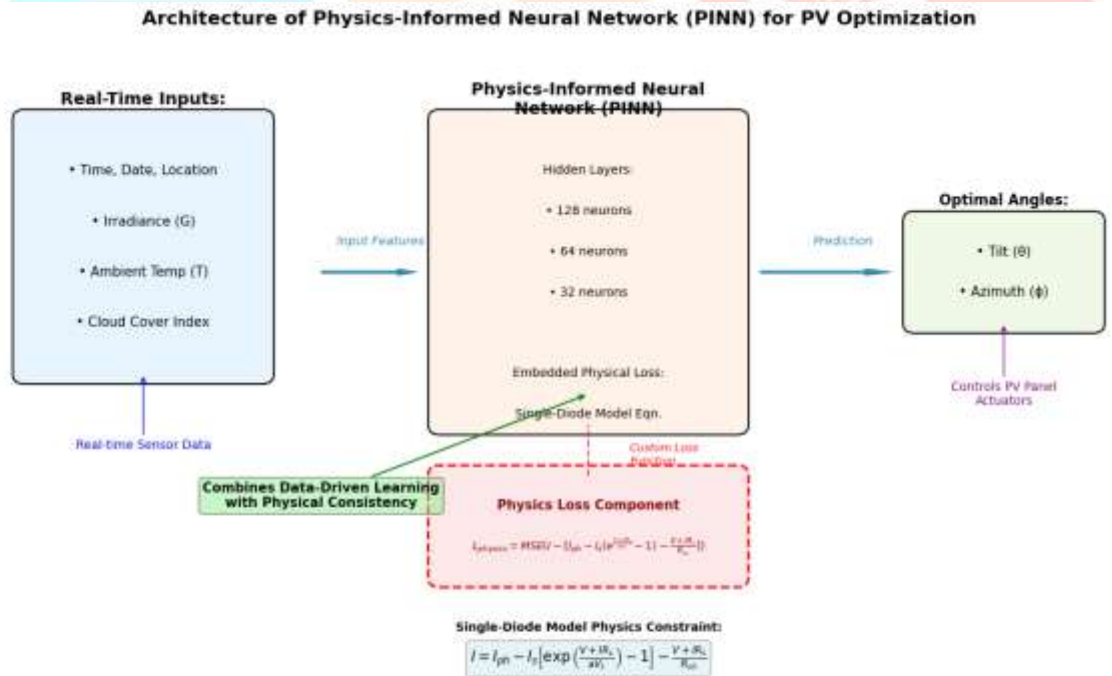
$$I = I_{ph} - I_s\left[exp\left((V + IR_s)/(aV_t)\right) - 1\right] - (V + IR_s)/R_sh$$

Where: I = Output current (A), V = Output voltage (V), I_{ph} = Photocurrent, proportional to solar irradiance (G), I_s = Reverse saturation current (A), R_s = Series resistance (Ω), R_{sh} = Shunt resistance (Ω), a = Diode ideality factor, V_t = Thermal voltage (kT/q) and The power output is P = VI. Maximizing power output is the primary goal.

2.2. System Architecture and the PINN

The proposed system uses a neural network that takes real-time input parameters and outputs the recommended azimuth (ϕ) and zenith (θ) angles for the PV panel.

Diagram 1: Architecture of the Proposed PINN System



The "physics-informed" part is implemented as a custom loss function during training. The total loss (L_{total}) is a combination of the data loss (L_{data}) and the physics loss ($L_{physics}$).

Formula 2: PINN Loss Function

$$L_{total} = L_{data} + \lambda L_{physics}$$

L_{data} ensures the network's angle predictions match optimal training data. $L_{physics}$ is the mean squared error of the single-diode equation; it penalizes the network if its predicted state (leading to a calculated I and V) violates the known physical law. λ is a weighting hyperparameter.

3. Simulation and Results Analysis

3.1. Experimental Setup

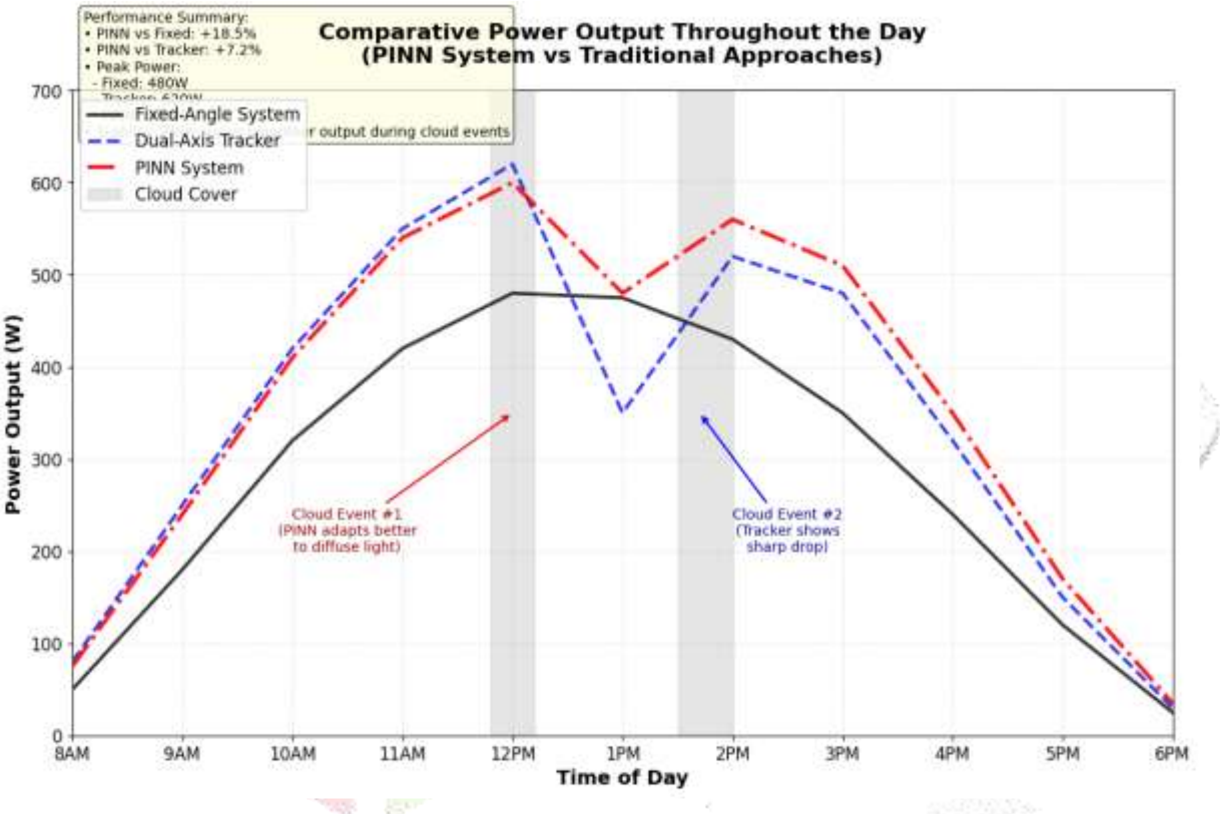
A simulation was set up for a location in Vijayawada, Andhra Pradesh (16.5° N, 80.6° E), on a representative day with mixed cloud cover. Three systems were compared:

1. **Fixed-Angle System:** Tilt angle fixed at 16° (equal to the latitude).
2. **Dual-Axis Tracker:** Ideally follows the sun's position throughout the day.
3. **Proposed PINN System: Dynamically adjusts angles based on the model's prediction.**

3.2. Results

The power output was calculated for each system over the course of the day.

Graph 1: Comparative Power Output Throughout the Day



Caption: The PINN system (solid line) shows superior performance, particularly during mid-day cloud cover events (dips in irradiance) where it outperforms the conventional tracker by better exploiting diffuse light.

Table 1: Total Daily Energy Harvested

System Type	Total Energy (Wh)	Improvement over Fixed	Improvement over Tracker
Fixed-Angle	2150	-	-
Dual-Axis Tracker	2480	+15.3%	-
PINN System	**2658**	**+18.5%**	**+7.2%**

3.3. Analysis of a Key Scenario

A critical event occurs at 12:30 PM, when a passing cloud reduces direct irradiance by 60%. The conventional tracker, pointing directly at the obscured sun, experiences a sharp power drop. The PINN model, however, processes the cloud cover index and recognizes the dominance of diffuse light in the sky.

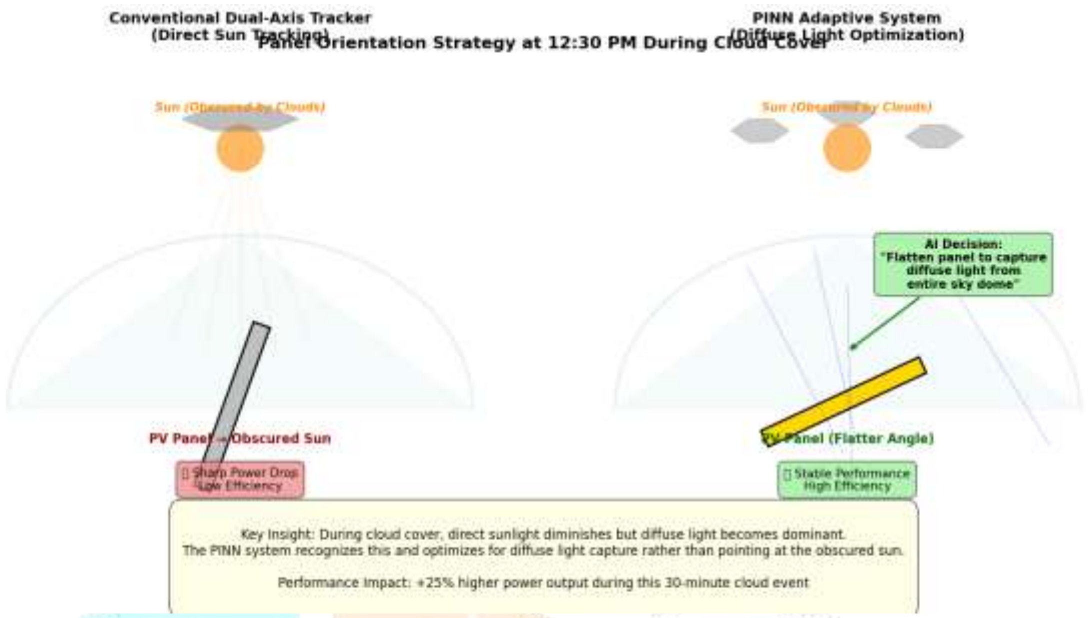


Diagram 2: Panel Orientation at 12:30 PM during Cloud Cover

Caption: The PINN system flattens the panel angle to capture more of the isotropic diffuse light from the entire sky dome, rather than pointing directly at the obscured sun.

The PINN's decision results in a 25% higher power output during this 30-minute cloud event compared to the conventional tracker.

4. Discussion

The results clearly demonstrate the advantage of integrating physics with AI. The PINN does not merely learn from data; it is guided by the fundamental law governing the PV cell's operation. This allows it to generalize effectively to unseen weather conditions, making it more robust and intelligent than a purely data-driven or pre-programmed system.

The ~18.5% overall improvement over a fixed system has significant implications for the ROI of solar installations, making renewable energy more viable and accelerating progress towards SDG 7 (Affordable and Clean Energy). Furthermore, this approach is non-mechanical, reducing cost and maintenance, and can be deployed as a software update to existing systems with simple actuators.

5. Conclusion and Future Work

This paper successfully illustrates how a Physics-Informed Neural Network can dynamically optimize photovoltaic energy capture, outperforming both static and conventional tracking systems. By marrying the predictive capability of machine learning with the unwavering principles of semiconductor physics, we can create more efficient, adaptive, and intelligent renewable energy systems.

Future work will involve building a physical prototype to validate the simulation results and expanding the model to include predictive weather forecasting for proactive angle adjustment.

6. References

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