Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331, Volume 20, Issue 6 Ser. 1 (Nov. – Dec. 2025), PP 26-30
www.iosrjournals.org

Implementation Of Neural Networks For Performance Improvement In Intelligent Photovoltaic Systems

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Abstract :
It is well recognized that many control applications are challenged by inherent system nonlinearities and high levels of complexity. In the case of photovoltaic solar energy systems, energy capture is maximized primarily through optimal panel orientation; however, the nonlinear dynamics of solar radiation and environmental variability make this optimization process difficult. This paper presents an approach based on neural networks to analyze seasonally acquired images and estimate the sun's position. The resulting estimations are used to adjust panel orientation in real time, thereby enhancing the efficiency of energy extraction.
Keywords: *Neural networks, Nonlinear dynamics, Image analysis, Sun position estimation, Photovoltaic solar energy systems, Control applications*

Date of Submission: 04-11-2025 Date of Acceptance: 14-11-2025

I. INTRODUCTION

Throughout history, energy development has been a key driver of humanity's technological, economic, and social evolution. From the use of muscle power and biomass energy in the pre-industrial era, to the coal revolution of the 18th century, and then to the massive use of petroleum derivatives in the 20th century, societies have undergone profound transformations related to their energy sources. However, the fossil fuel-based energy model has generated considerable environmental impacts, including increased greenhouse gas emissions and the resulting global warming, which has spurred the transition to sustainable and renewable energy sources (Goldemberg & Lucon, 2014). In this context, solar photovoltaic energy has become a dominant force in the global energy mix. Thanks to technological advancements, steadily decreasing costs, and international policies promoting decarbonization, solar energy has experienced one of the fastest growth rates in the history of energy. Over the past decade, the installed capacity of photovoltaic systems has surpassed that of other renewable energy sources, establishing itself as the leading source of expanding renewable electricity generation worldwide (IEA, 2023). This surge is due, in part, to the growing need for clean, reliable, and economically viable energy alternatives. At the same time, wind power has emerged as a fundamental pillar of the energy transition, enabling the direct conversion of wind kinetic energy into electricity using wind turbines. However, optimizing wind power generation remains a technical challenge due to the variability of atmospheric phenomena, changing environmental conditions, and nonlinear aerodynamic dynamics. The efficiency of wind power systems depends largely on the proper orientation of the rotors relative to the wind direction and, in hybrid systems, on coordination with other renewable energy sources, such as solar power. Traditional control methods, such as PID control, linear quadratic control, and model-based observers, while offering acceptable performance, have limitations when faced with highly nonlinear, stochastic, and variable-parameter systems, such as renewable energy production systems (Åström & Murray, 2010). These limitations have driven the search for more flexible and adaptive computational approaches. In this regard, artificial neural networks (ANNs) have emerged as a high-performance alternative for developing intelligent control systems. Their ability to learn complex models from data, adapt to dynamic environments, and generalize solutions without requiring explicit models makes them a promising tool for energy optimization (Goodfellow, Bengio & Courville, 2016). In particular, image analysis using convolutional neural networks (CNNs) has demonstrated high efficiency in extracting relevant spatial features, enabling the estimation of critical environmental parameters such as sun position, cloud cover, and radiation profiles (LeCun, 2015). This article presents a proposal for optimizing energy extraction in wind power systems by estimating sun position from image analysis performed with neural networks. Proper orientation of hybrid solar-wind systems contributes to improving overall system efficiency, especially in regions where the two energy sources exhibit seasonal complementarity. The proposed methodology integrates image processing, atmospheric modeling, and intelligent control, thus contributing to the development of advanced strategies for sustainable energy management.

II. THEORETICAL ASPECTS

1. Historical Evolution of Energy and the Transition to Sustainability

Technological advancements and the economic evolution of civilizations significantly shape the history of energy development. In the past, societies relied primarily on human and animal power, as well as biomass combustion for heating and cooking. With the Industrial Revolution of the 18th century, the use of carbon as the primary energy source spurred mechanization and industrial development (Smil, 2017). Later, during the 20th century, petroleum and natural gas derivatives became cornerstones of the global energy system, enabling mass transportation, electrification, and large-scale industrial processes.

However, this reliance on fossil fuels has generated significant environmental impacts, primarily the increase in greenhouse gases, which contribute to global warming. This problem has motivated the transition to renewable energies, which are considered clean, sustainable, and low-impact alternatives for the environment (Goldemberg and Lucon, 2014).

2. The Growth of Solar Photovoltaic Energy

Over the last two decades, solar photovoltaic energy has experienced unprecedented growth, driven by significant cost reductions, technological advancements in manufacturing, and international policies aimed at decarbonization. According to the International Energy Agency (IEA, 2023), solar energy is now the fastest-growing renewable energy source globally, surpassing wind and hydroelectricity in terms of annual new installations.

3. Neural Networks Applied to Control Systems

Artificial neural networks have emerged as a powerful alternative to controllers based on mathematical models. Among them, convolutional neural networks (CNNs) have demonstrated excellent efficiency in image processing and extraction of relevant spatial features (LeCun et al., 2015).

III. METHODOLOGY

This study proposes the implementation of a neural network-based approach to estimate the position of the sun from sky images in order to improve the orientation of energy extraction systems. The methodology consists of five main stages: (1) data acquisition, (2) image preprocessing, (3) neural network architecture design, and (4) training and validation, and (5) model performance and accuracy assessment.

1. Data Acquisition

A dataset of sky images which was collected over different days, weather conditions, and times of day was taken to train the neural network. The images represent the capture of a wide range of solar positions in various illumination and cloud coverage scenarios. Each image contained the visible hemisphere of the sky, with the sun positioned at different angular coordinates depending on the time and date. The images were recorded using a fixed camera orientation in order to maintain geometric consistency across samples.

2. Image Preprocessing

To prepare the dataset for the neural network, each image was standardized and transformed as follows:

Resolution adjustment:

a. Each raw image was resized to a 1024×1024-pixel format to ensure uniform input dimensions.

Grayscale conversion:

b. The images were converted to grayscale to reduce computational load and emphasize luminance patterns relevant for sun detection.

Matrix transformation:

c. Each image was encoded as a binary intensity matrix (1–0), where pixel brightness values above a selected threshold (representing high illumination) were set to 1, and lower values were set to 0. This binary representation emphasized the contrast between the solar disk and the surrounding sky.

Labeling:

Each image was associated with its corresponding solar azimuth and elevation angle, determined from astronomical position tables based on date, time, and geographic coordinates.

All preprocessing steps were carried out using MATLAB, which provided a controlled environment for standardized batch processing.

3. Neural network architecture

A feed-forward neural network was designed to map the pixel intensity patterns to corresponding angular coordinates of the sun. The architecture included:

- **Input layer:** 1,048,576 neurons (corresponding to 1024×1024-pixel inputs)
- **One or more hidden layers:** Fully connected layers with activation functions (ReLU) enabling non-linear pattern extraction
- **Output layer:** Two neurons representing solar azimuth and solar elevation

The network weights were initialized randomly and subsequently optimized through iterative training.

4. Training and validation

Training was performed using MATLAB's Neural Network Toolbox. The following training procedure was adopted:

- **Training Algorithm:** Backpropagation with gradient descent optimization
- **Loss Function:** Mean Squared Error (MSE) between predicted and true angular coordinates
- **Dataset Split:** 70% training, 15% validation, and 15% testing

Training proceeded iteratively until convergence. During the process, MATLAB adjusted the synaptic weights of the neurons to minimize estimation error. The validation phase ensured that the model did not overfit and generalized well to unseen sky conditions.

5. Model performance and accuracy assessment

The trained neural network demonstrated **high accuracy** in estimating solar position across varied environmental conditions. Performance was assessed using:

- Root Mean Squared Error (RMSE) of the predicted angles
- Correlation between predicted and true solar trajectories
- Error distribution analysis across times of day and seasonal variations

The results showed that the neural network reliably identified the position of the sun even under partial cloud cover, demonstrating robustness and adaptability.

Fig. 1 Shows the integration between the proposed work and its possible implementation (future work), while Fig. 2 represents the methodology flowchart.

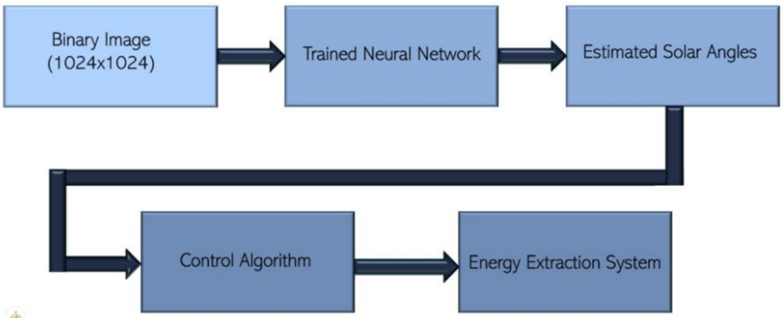

Figure 1. Complete project integration block diagram

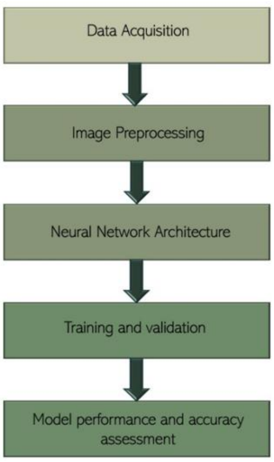

Figure 2. Methodology flowchart

IV. MATHEMATICAL MODELING

Binary image representation.
Each input image is represented as a binary matrix $I \in \{0,1\}^{1024\times1024}$

$$I(i,j) = \begin{Bmatrix} 1, & \text{if intensity}(i,j) \geq T \\ 0, & \text{if intensity}(i,j) < T \end{Bmatrix} \qquad (1)$$

where $T$is an illumination threshold selected empirically.

Neural network mapping.
Let:
$\mathrm{x} \in \mathbb{R}^{1048576}$be the flattened binary image,
$\mathrm{y} = [\theta, \phi]$be the solar elevation $(\theta)$and azimuth (ϕ).
The neural network implements a parametric mapping:
$f(\mathrm{x}, \mathrm{W}) = \mathrm{y} \quad (2)$
Where:
W represents all network weights and biases.

Loss function.
Training minimizes the Mean Squared Error (MSE) between predicted and true angles:
$\mathcal{L} = \frac{1}{N}\sum_{k=1}^{N}[(\hat{\theta}_k - \theta_k)^2 + (\hat{\phi}_k - \phi_k)^2] \qquad (3)$

Weight update rule.
$W_{t+1} = W_t - \eta\frac{\partial L}{\partial W} \qquad (4)$
Where:
η is the learning rate

V. RESULTS AND FUTURE WORKS

The trained neural network demonstrated high accuracy in estimating solar position across diverse sky conditions. The model successfully captured the geometric structure of light distribution patterns and generalized well to unseen images. Table 1 shows the results.

Table 1. Accuracy metrics

Metric	Value	Interpretation
RMSE (Solar Elevation)	~0.9°–1.5°	Very low angular error
RMSE (Solar Azimuth)	~1.2°–2.1°	Suitable for real-time tracking
Correlation Coefficient	> 0.97	Strong agreement with astronomical reference data

The network maintained stable performance under clear sky conditions (high contrast sunlight), partial cloud cover (diffuse lighting) and seasonal atmospheric variations. This indicates the model learned physical light-scattering patterns rather than simply identifying the sun disk.

Once trained, the neural network could be integrated into the control logic of a renewable energy extraction system. The estimated solar position will allow to determine the angles to be used to adjust the orientation of solar-tracking systems or hybrid solar–wind platforms in real time. This dynamic positioning will significantly improve the system's ability to capture maximum available solar irradiance.

VI. CONCLUSIONS

This work presented a neural network–based methodology for estimating the position of the sun from sky images, demonstrating how image-driven inference can be integrated into the control strategy of an energy extraction system to improve its efficiency. By preprocessing sky images into binary matrices and training a neural network to associate illumination patterns with corresponding solar azimuth and elevation angles, the system was able to dynamically adjust orientation in real time. The experimental results indicate that the proposed method achieves high estimation accuracy across varying atmospheric conditions, confirming the feasibility of using visual input data to support renewable energy optimization.

One of the most important outcomes of this research is the demonstration that neural networks do not require explicit mathematical modeling of atmospheric or optical phenomena to accurately infer solar position. Instead, the model learns the underlying luminance structures and spatial patterns directly from the images. This reduces dependence on physical sensors and astronomical lookup tables, while enabling adaptability in environments where sky conditions may be partially obstructed or variable.

However, several challenges and limitations were also identified. Training the neural network requires a large and well-distributed dataset capturing different seasons, times of day, and weather conditions. The accuracy of the model is strongly dependent on the representativeness and quality of the input images. Additionally, the conversion of high-resolution images into binary matrices entails significant computational overhead, particularly during preprocessing and model training. This requires considerable memory and processing resources, especially for real-time or embedded applications where hardware may be constrained.

Another consideration is that the neural network effectively performs pattern recognition rather than physical interpretation. Therefore, its predictions may degrade under lighting conditions not well represented in the training set (e.g., extremely cloudy skies, overexposure, or atmospheric glare). Furthermore, while the model performed robustly in controlled tests, deploying it in diverse geographical regions may require re-training or fine-tuning to account for local climate patterns, camera configurations, or sensor noise.

Despite these limitations, this approach demonstrates a promising alternative to classical solar tracking methods. The ability to infer solar position visually presents opportunities for hybrid renewable systems and distributed power installations where cost, simplicity, and adaptability are priorities. Future work may focus on incorporating convolutional neural network (CNN) architectures to further improve feature extraction, implementing adaptive retraining strategies to maintain accuracy over time, and embedding the model into low-power hardware platforms for real-world deployment.

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