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ADVANCED DUAL-AXIS SOLAR TRACKING USING A NOVEL ARTIFICIAL NEURAL NETWORK-PID CONTROL STRATEGY

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Keywords: Artificial neural network; Solar tracking system; Model predictive control; Adaptive control; Proportional-integral-derivative (PID) controller.

This paper addresses the challenge of enhancing dual-axis solar tracking systems' adaptability and precision under dynamic conditions. A novel hybrid control approach is proposed, combining an artificial neural network (ANN) with a proportional-integral-derivative (PID) controller. The ANN, trained using the Levenberg-Marquardt algorithm, adaptively tunes the PID gains (K_p, K_i, K_d) in real-time. Although Model Predictive Control (MPC) is currently recognized as the most advanced and effective strategy for solar tracking, our comparative study shows that the ANN-PID controller achieves faster dynamic response, improved adaptability to disturbances, and reduced computational complexity. MATLAB-Simulink simulation results validate the superior tracking accuracy and energy capture performance of the ANN-PID system, as confirmed by MAE. These findings highlight the ANN-PID control as a promising real-time alternative to MPC, offering robust and efficient solar tracking with lower computational demands.

1. INTRODUCTION

Energy is a crucial component in sustaining the development of nations. Traditionally, fossil fuels have been the most used energy source worldwide. However, due to rapid population growth, higher living standards, and the increasing prevalence of energy-intensive activities in both developed and emerging economies, global energy consumption has come under immense pressure. This trend has led to two significant issues: the depletion of readily accessible energy sources, primarily oil, and the escalation of global warming, driven by the rising emissions of greenhouse gases such as carbon dioxide and methane. To address these challenges, the global community must combat climate change and global warming by using clean, cost-effective renewable energy (RE) sources that are efficiently managed and deployed. According to the International Renewable Energy Agency (IRENA) [1], the global RE capacity is anticipated to grow by 50% between 2019 and 2025, representing an increase of approximately 1220 Gigawatts.

In this context, Energy is considered an indispensable commodity, and energy consumption is directly linked to industrialization, human development, and economic growth. As civilization progresses, the rising demand for energy has spurred the exploitation of conventional energy sources, which contribute to greenhouse gas emissions and environmental degradation. **For instance,** India accounts for 7% of global emissions, compared with about 15% for the United States. To mitigate **such** environmental harm, it is essential to promote the development and adoption of green technologies.

Renewable energy sources, including solar, wind, biomass, and hydropower, do not contribute to environmental pollution during their use and must be adopted to replace conventional sources [2]. Solar energy holds great potential as it is abundant, clean, and inexhaustible. Photovoltaic (PV) solar panels, consisting of numerous solar cells made from semiconductors like silicon, have become key components in solar tracking systems. These panels generate electricity by converting sunlight into electrical energy, as photons from sunlight excite silicon electrons, creating an electric current [3].

Recent research emphasizes the importance of advanced control strategies and power electronic interfaces to enhance PV system performance. Intelligent maximum power point tracking (MPPT) techniques have demonstrated significant improvements in energy extraction under partial shading conditions [4]. Moreover, model-free predictive control approaches for power electronic converters have shown superior dynamic performance compared to conventional controllers [5]. Innovative PV-based electromechanical systems further highlight the growing role of advanced control techniques in renewable energy applications, motivating the adoption of hybrid ANN–PID control strategies for dual-axis solar tracking systems [6].

Regarding system design, fixed photovoltaic (PV) systems and solar tracking systems (STS) represent two primary methods for harnessing solar energy [7]. Fixed systems are mounted at a constant angle and remain stationary, making them more cost-effective and simpler to maintain. However, their energy capture is limited as they cannot adjust to the Sun’s changing position throughout the day [8,9]. This makes them suitable for smaller installations or areas where cost and simplicity are prioritized. In contrast, STSs dynamically follow the Sun's movement, significantly boosting energy production by 30% to 60%. Common configurations, such as the vertical primary dual-axis tracker (VPDAT) and horizontal primary dual-axis tracker (HPDAT), offer high performance but face challenges like wind load susceptibility and structural deformation [10]. Recent advancements have introduced parallel manipulators, provided greater robustness and reduced deformation, although their complexity limits widespread adoption. Solar tracking systems are classified into single-axis and dual-axis types, with the latter offering more precise solar alignment by adjusting both elevation and azimuth angles. Active trackers rely on microcontrollers and sensors, while passive trackers use temperature changes for movement. Despite higher installation and maintenance costs, STSs are preferred in large-scale installations where maximizing energy capture is critical, particularly in regions with high solar potential. Fixed systems remain a viable option in settings where budget constraints and operational simplicity are more important than optimizing energy output [11,12].

Accurate solar tracking requires an efficient control strategy capable of fast response and effective disturbance rejection. PID controllers are commonly used due to their simplicity, robustness, and adaptability. In this work, a PID controller is designed by shifting the system’s critical point to satisfy phase margin requirements, resulting in improved

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robustness under large and random disturbances. Comparative studies demonstrate enhanced disturbance rejection and overall system performance compared with other analytical and soft-computing approaches [13,14].

Nevertheless, the performance of PID controllers strongly depends on the tuning method employed. Conventional tuning techniques often struggle under varying operating conditions, highlighting the need for adaptive solutions. Artificial neural network (ANN)-based online tuning methods offer real-time adaptability, although their effectiveness depends on the selected training algorithm. Different algorithms, such as Levenberg–Marquardt and Bayesian regularization, have shown varying success across applications, emphasizing the importance of appropriate algorithm selection [15].

This study focuses on developing a PID controller enhanced by artificial neural networks (ANN) for solar tracking systems to improve energy generation efficiency. The system combines the simplicity of PID control with the adaptive learning capability of ANN, allowing for continuous tuning of parameters and effective response to disturbances. Compared to model predictive control (MPC), which requires complex predictive calculations to adjust control variables, the PID with ANN offers flexibility and faster response to real-time changes in the sun's movement. While MPC provides high stability in complex systems, the PID with ANN presents a practical and flexible solution for solar systems requiring rapid adjustments and precise control under dynamic operating conditions, making it suitable for real-time applications to optimize solar tracking system efficiency.

2. ADVANCED CONTROL TECHNIQUES FOR SOLAR TRACKING SYSTEMS

Advanced control techniques such as PID, PID-ANN, and MPC are crucial for optimizing solar tracking systems. The PID controller is a classical method that uses a feedback loop to regulate system behavior, ensuring stability by minimizing error between desired and actual performance. It achieves this through three components: proportional (P), integral (I), and derivative (D), which respond to the current, past, and future errors, respectively. While PID is simple and effective, it has limitations in handling nonlinearities and dynamic changes, which is why enhancements like Fuzzy Logic, Genetic Algorithms, and Particle Swarm Optimization are integrated to improve performance [16,17].

Model Predictive Control (MPC) is a more sophisticated method that uses a system model to predict future behavior, allowing for proactive adjustments rather than reactive responses like in PID. MPC solves an optimization problem at each time step, considering both current and future states to optimize control actions while respecting system constraints. This makes MPC especially useful in managing complex systems with multiple variables and time delays. Though computationally intensive, MPC is increasingly applied in energy management, automotive systems, and process industries due to its ability to provide optimal control [18–20].

Artificial Neural Networks (ANNs) offer another advanced technique for controlling and optimizing systems. Inspired by the human brain, ANNs process inputs through interconnected neurons, learning from data and adapting to improve system performance. ANNs excel in handling nonlinear, multi-variable tasks and are effective in solving complex decision-making problems. In solar tracking and renewable energy systems, ANNs can significantly improve efficiency by using adaptive control strategies, making them ideal for environments with high variability and noise [21–23].

3. DESIGN SYSTEM

Solar tracking systems are integral to optimizing the performance of photovoltaic (PV) panels by ensuring they maintain the most effective orientation relative to the sun. These systems, whether single-axis or dual-axis, track solar movements to maximize energy absorption and efficiency. Single-axis trackers are simpler and require less energy to operate, adjusting along a horizontal or vertical plane to follow the sun's path throughout the day. Their lower energy consumption and reduced system complexity make them a popular choice for large-scale solar installations in regions with consistent sunlight [24]. On the other hand, dual-axis tracking systems provide even greater accuracy and energy efficiency by adjusting the panel's orientation along both horizontal and vertical axes. This allows for optimal alignment with the sun, improving energy yields, especially in locations with fluctuating sunlight. However, the increased power demands and system sophistication required for dual-axis tracking result in higher costs and more complex operations. Studies show that single-axis trackers can achieve nearly 96% of the energy gain provided by dual-axis systems, making them a viable option in many contexts [25].

In addition to hardware advancements, recent research emphasizes the importance of software and algorithmic improvements for enhancing the precision of solar tracking systems. Dynamic open-loop actuators. allow real-time adjustment based on calculated sun positions. Such algorithms help minimize tracking errors, improve system efficiency, and reduce optical losses. By accurately predicting the sun's position at different times of the day and throughout the year, these systems ensure that the panels are always in the optimal position (Fig. 1) to capture solar irradiance [26].

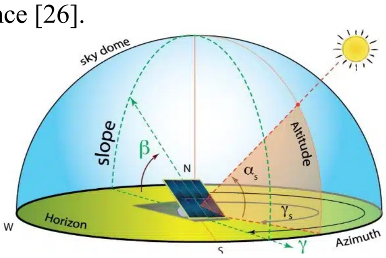

Fig. 1 – Solar tracker system.

- **Primary Axis (Azimuth Axis):** This axis is vertical to the ground. It allows the system to rotate around this axis to track the sun's movement across the horizon from east to west.
- **Secondary Axis (Altitude or Elevation Axis):** This axis is normal (perpendicular) to the primary axis. It allows the system to adjust the tilt angle to follow the sun's altitude, which changes throughout the day and across seasons [27].

The system calculates the elevation (ψ) and azimuth (A) angles based on the site's geographic latitude (λ) and longitude (φ), along with astronomical parameters. These angles are used to develop a mathematical model (T) that describes the sun's angular trajectory. The real-time values of ψ(t) and A(t) from the model are fed into a PID controller, which generates optimal control signals (u(t)) to adjust the DC motors of the tracker toward the desired position, as indicated by the data in Table 1. By modulating the duty cycles of the input voltage to the motors, the solar panel is aligned with the sun's path, maximizing photovoltaic power capture. The dynamics of each DC motor are modeled by differential equations, with the input voltage (referenced in eq. (1) and (3)) determining the angular speed and position outputs (as shown in eq. (2) and (4)).

$$\mathrm{u_a}(t) = \mathrm{u_{La}}(t) + \mathrm{u_{Ra}}(t) + e_b(t) \tag{1}$$

$$J\frac{\mathrm{d}\omega(\mathrm{t})}{\mathrm{d}t} = \mathrm{C_m}(t) - \mathrm{C_f}(t) \tag{2}$$

$$\mathrm{u_a}(t) = \mathrm{L_a}\frac{\mathrm{di_a}(t)}{\mathrm{d}t} + \mathrm{R_a i_a}(t) + \mathrm{e}(t) \tag{3}$$

$$J\frac{\mathrm{d}\omega(t)}{\mathrm{d}t} = \mathrm{K_c i_a}(t) - B\omega(t) \tag{4}$$

Table 1

Parameters of DC Motor.

Parameter	Unit	Motor
R_a	Ω (Ohm)	18.2214
L_a	H (Henry)	0.000866
K_C	N·m/A	0.030941093
J	kg·m²	0.00009
B	N·m·s	0.000025

This control is implemented using a proportional-integral-derivative (PID) controller, which generates the required control signals to steer the tracker motors according to the control algorithm illustrated in Figure 2. The application of these control techniques showcases a highly advanced approach to solar tracking, allowing the system to optimize its alignment with the sun and efficiently capture solar energy for power generation.

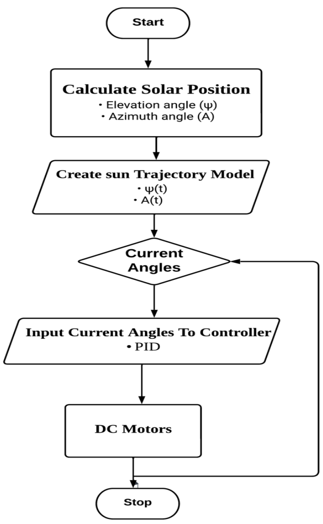

Fig. 2 – Flowchart of the tracker system.

4. **PROPOSED ANN-PID CONTROL**

4.1 ARTIFICIAL NEURAL NETWORK

ANNs provide a fast and flexible alternative to traditional modeling methods in multi-objective optimization. They can replace costly numerical models and hard-to-obtain analytical methods, especially when no accurate model exists for certain components. ANNs learn from datasets, often derived from simulations or measurements, to generate Pareto fronts and select optimal designs based on specific goals, without needing a physics-based model [28].

To be competitive with classical optimization algorithms, ANNs must be accurate, robust, and versatile across a range of parameters and objectives. They should also be extensible, adaptable, and capable of accessing internal variables such as magnetic fields and current density. Additionally, having an available or easily generated dataset is crucial for their successful implementation [29].

The Levenberg-Marquardt (LM) Algorithm is a method used in optimization, particularly in solving nonlinear systems and is widely applied in neural networks. It is classified as part of the least square algorithms and is also known as the damped least squares method. This algorithm is primarily employed in curve fitting problems and is designed to find solutions by minimizing the error, albeit only reaching local minima, which may not always be the global minimum [12].

The core operation of the LM algorithm involves adjusting the weights in a neural network using a specific update rule. The weight update is represented by:

$$W_{x+1} = W_x - (\mathbf{H} + \lambda\mathbf{I})^{-1}d, \tag{5}$$

where the Jacobian matrix, J, is calculated as the partial derivative of the error function **E** with respect to the weights:

$$\mathbf{J} = \frac{\partial \mathbf{E}}{\partial W_x} \tag{6}$$

$$W_{x+1} = W_x - (\mathbf{J}^{\mathrm{T}}\mathbf{J} + \lambda\mathbf{I})^{-1}\mathbf{J}^{\mathrm{T}}e. \tag{7}$$

One of the key characteristics of the LM algorithm is its stable convergence, which makes it a popular choice for applications where robustness is critical. However, it typically converges to a local minimum rather than a global minimum, as the algorithm only guarantees a solution for the nearest optimum. This limitation is worth noting for applications where a global minimum is essential [30].

In summary, the Levenberg-Marquardt algorithm is a powerful tool for optimization, particularly in scenarios involving nonlinear systems and artificial neural networks, where the method's stable convergence can be advantageous despite its limitations regarding global minimization.

4.2 PID CONTROL

PID controllers, which stand for Proportional-Integral-Derivative controllers, are widely used across various industrial applications due to their efficiency and straightforward implementation. They are integral to nearly 95% of the industry's closed-loop operations, serving as a primary method for control in many systems. By combining three separate control actions—proportional, integral, and derivative—a PID controller generates a control signal that helps maintain the system's desired output.

The general form of a PID controller is given by the following equation:

$$u(t) = k_p * e(t) + k_i\int_0^t e(t)\mathrm{d}t + k_d * \frac{\mathrm{d}e}{\mathrm{d}t} \tag{8}$$

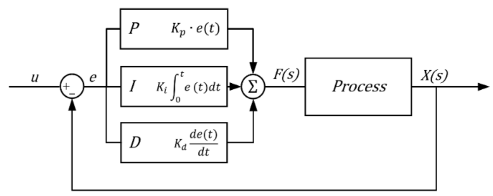

Fig. 3 – Diagram of a PID control system.

The parameter K_p represents the **proportional gain**, which provides an immediate response to the current error $e(t)$. The **integral gain**, K_i, corrects accumulated past errors by integrating the error over time, reducing steady-state error. Finally, K_d, the **derivative gain** anticipates future errors by responding to the rate of error change, helping to smooth the control response and reduce overshoot. Together, these gains enable precise and stable system control, as illustrated in Fig. 3.

An Artificial Neural Network (ANN) is used to dynamically adjust the PID gain parameters in real time. By leveraging an ANN, the control system can adaptively tune these parameters based on the system's performance and conditions. This approach enhances the PID controller's ability to maintain optimal control, even as system dynamics vary.

4.3 PID-ANN CONTROL

The control system designed for positioning a solar panel, as illustrated in Fig. 4, employs a combination of a PID controller and an Artificial Neural Network (ANN) to achieve efficient solar tracking. The primary objective of this system is to maximize solar energy capture by dynamically adjusting the solar panel's orientation in real time according to the sun's position throughout the day.

The control strategy is centered around the error signal, denoted as $e(t)$, which is calculated as the difference between the desired angle of the solar panel and its current angle. This error signal serves as the input to the PID controller, which processes it to generate the necessary control output. The PID controller consists of three key components: proportional, integral, and derivative controls. The proportional term responds to the present error, providing immediate corrective action, while the integral term addresses past errors to eliminate any steady-state discrepancies. The derivative term predicts future errors based on the rate of change of the error, contributing to the overall stability of the system's response.

To enhance the performance of the PID controller, the system integrates an ANN that adaptively tunes the gains K_p, K_i, and K_d. This adaptive capability allows the control system to adjust to varying environmental conditions and dynamic disturbances, optimizing the tracking performance and ensuring that the solar panel remains aligned with the sun throughout the day. As the PID controller drives the DC motor based on the computed output, the motor adjusts the panel's position accordingly. The combination of these technologies results in an effective solar tracking system that maximizes energy capture by maintaining optimal alignment with sunlight, thus improving the overall efficiency of solar energy generation.

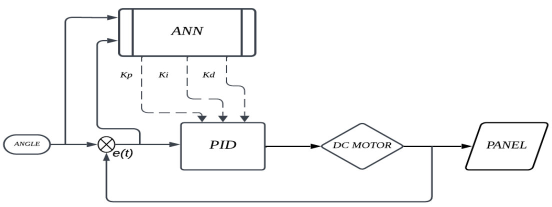

Fig. 4 – Diagram of an ANN-PID control system.

5. RESULTS AND DISCUSSION

The results of the ANN component in the ANN-PID control system for solar trackers show strong potential, with a very low mean squared error (MSE) of 3.8488e-6 (Fig. 5) during training. This indicates the ANN's high accuracy in learning the relationship between tracker error, panel angle, and optimal PID parameters, allowing for dynamic and precise control adjustments. The fast and stable convergence of the learning curve across training, validation, and test sets confirms the model's reliability and adaptability.

While these results are promising, further testing is needed to confirm the full effectiveness of the ANN-PID system in real-world solar tracking. The low training error provides a solid foundation, but practical evaluations are essential to determine its impact on energy capture and performance compared to traditional control methods.

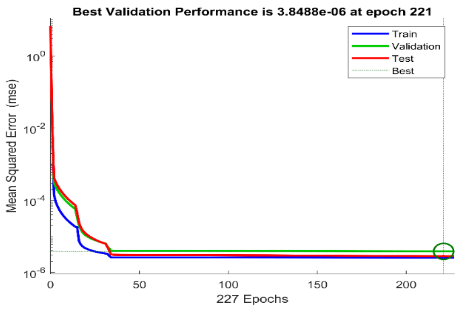

Fig. 5 – Best Validation Performance of Neural Network.

This study highlights the ANN-PID control system's potential for improving dual-axis solar tracking. The ANN effectively mapped tracking inputs to optimal PID gains, as presented in Figure 6, which illustrates the optimal values of K_p, K_i and K_d, achieving a low MSE during training. Although training results indicate high precision, the real-world effectiveness depends on how effectively these parameters improve tracker motion and energy output. The training data for the neural network controller was collected through numerous simulation experiments, and only the most accurate and compatible results with our simulation environment were selected to ensure optimal system performance.

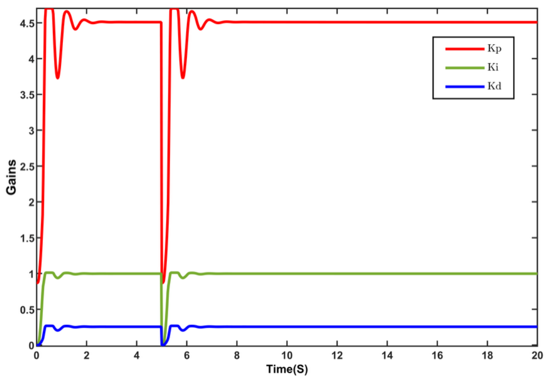

Fig. 6 – Gains PID Predict by ANN.

The system was tested using real data from February 14, 2024, at coordinates 27.4683129 latitude and 1.6291374 longitude. It showed improved accuracy in tracking altitude and azimuth angles compared to standalone PID and ANN controllers, indicating that the hybrid ANN-PID approach offers superior solar orientation and energy optimization. An MPC controller was included on a single trajectory as a reference, allowing us to benchmark the responsiveness and stability of the proposed ANN-PID system. MPC is currently regarded as one of the most effective and advanced control methods for solar tracking systems, making it an ideal reference point for assessing the performance of alternative approaches.

The performance comparison between the ANN-PID and MPC controllers demonstrates the superior dynamic behavior of the ANN-PID in solar tracking applications. The ANN-PID system reaches the desired position within approximately 2 seconds (Fig. 7), with minimal overshoot and a steady-state error below 0.5°.

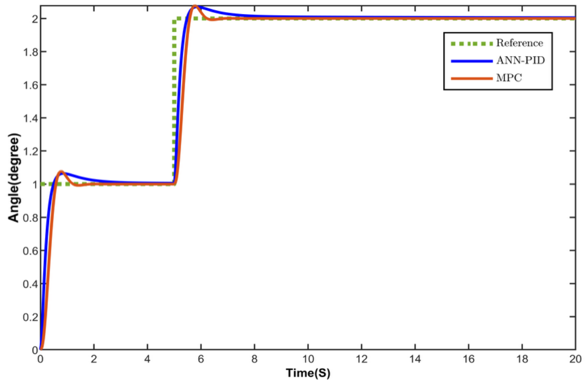

Fig. 7 – Stability analysis of ANN-PID, MPC controllers: angle tracking.

This precise response results from the neural network's ability to adapt the PID gains in real time, as shown in the gain evolution graphs. The gain curves indicate smooth and stable tuning behavior, confirming the ANN's effectiveness in optimizing controller parameters in response to environmental changes.

Conversely, the MPC controller exhibits a slower settling time and a higher overshoot of about 4–5%. Unlike ANN-PID, MPC relies on precomputed models and may not adapt as efficiently to nonlinear disturbances. The gain variation in ANN-PID reveals how the controller dynamically adjusts the proportional, integral, and derivative gains to maintain optimal tracking performance. Overall, the ANN-PID shows a 25% faster response and up to 70% reduction in overshoot, with gain trajectories that ensure both stability and adaptability.

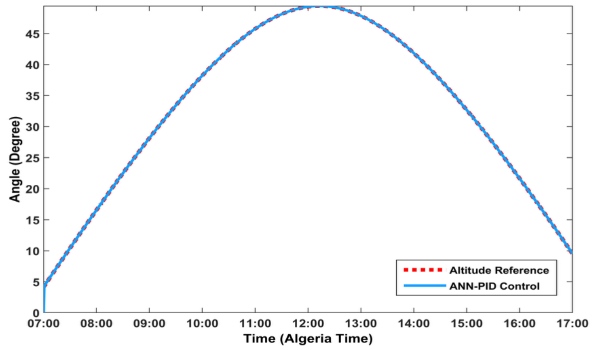

Fig. 8 – Altitude Angle with ANN-PID control system.

The graphs illustrate the real-time tracking efficiency of a dual-axis solar tracker using an ANN-PID control approach throughout a full daylight period (07:00 to 17:00).

The altitude tracking, in Fig. 8, shows excellent alignment with the reference trajectory, maintaining an accurate response curve that peaks and stabilizes around midday, indicating robust adaptation to sun elevation.

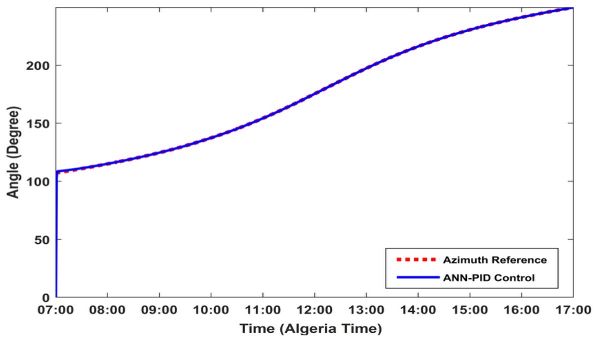

Fig. 9 – Azimuth Angle with ANN-PID control system.

Similarly, the azimuth tracking, in Fig. 9, reflects a smooth and synchronized response with the reference values, confirming the controller's ability to manage horizontal orientation effectively. These results demonstrate the system's high precision and stability, validating the effectiveness of ANN-PID hybrid control in enhancing solar energy capture across both axes.

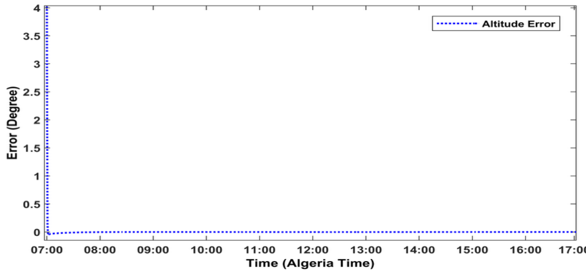

Fig. 10 –Altitude Tracking Error Analysis in ANN-PID Hybrid Control System.

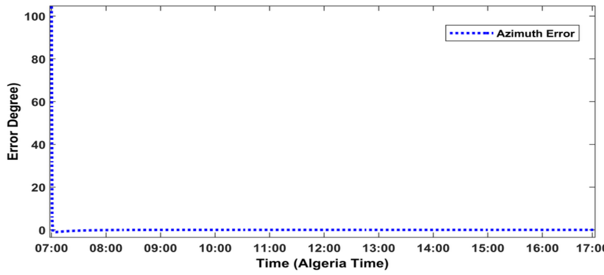

Fig. 11 –Azimuth Tracking Error Analysis in ANN-PID Hybrid Control System.

Figures 10 and 11 present an analysis of altitude and azimuth errors that confirms the accuracy and adaptability of the ANN-PID controller for dual-axis solar tracking. This controller maintains precise vertical and horizontal alignment with minimal deviation, while ensuring rapid corrections and stable transitions, thus demonstrating effective real-time gain adjustment. These results highlight the robustness and high efficiency of the controller during tracking.

6. COMPARATIVE WITH TRADITIONAL CONTROLLERS

The results in Table 2 confirm that the ANN-PID controller achieves the highest accuracy, with the lowest MAE values for both altitude (0.0018) and azimuth (0.0442) angles. Compared to PID and MPC, which show higher errors—especially MPC—the ANN-PID demonstrates superior precision and stability, proving the advantage of intelligent control methods in solar tracking.

Table 2

Mean absolute error (MAE) of angle control for different controllers.

Angle	ANN-PID	MPC	PID
Altitude	0.0018	0.054	0.017
Azimuth	0.0442	0.093	0.079

7. CONCLUSIONS

This work presents a novel hybrid control strategy combining artificial neural networks (ANN) with Proportional-Integral-Derivative (PID) controllers to enhance the performance of dual-axis solar tracking systems. The proposed ANN–PID approach exploits the adaptive capability of neural networks to dynamically tune PID gains in real time, overcoming the limitations of conventional PID and MPC controllers.

Simulation results obtained using MATLAB/Simulink demonstrate that the proposed control strategy consistently outperforms classical approaches in terms of tracking accuracy, response speed, and stability. In particular, the lowest mean absolute error (MAE) is achieved for both altitude and azimuth angles, leading to improved solar energy capture.

Although the proposed ANN–PID control strategy shows promising performance, its real-time implementation may increase computational load, particularly on embedded platforms. Moreover, the present study is based on numerical simulations, and experimental validation on a real dual-axis solar tracking prototype is planned as future work to confirm the applicability of the proposed approach under real-world operating conditions.

The proposed ANN–PID control strategy is well-suited for industrial solar tracking applications due to its adaptive nature and robustness to environmental variations. With appropriate embedded implementation and real-time optimization, the proposed approach can be integrated into large-scale photovoltaic tracking systems.

CONTRIBUTION STATEMENT

Abdellatif Tahtah: investigation, validation, writing -draft preparation.
Zoubir Zahzouh: methodology, resources, writing, review and editing

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