DOI: https://doi.org/10.54966/jreen.v1i1.1242



Journal of Renewable Energies

Revue des Energies Renouvelables journal home page: https://revue.cder.dz/index.php/rer



Conference paper

Robust Solar Tracking with Neural Network Predictive Modeling and Sliding Mode Control

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| ARTICLE INFO | ABSTRACT |
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| Article history: Received July 31, 2024 Accepted September 4, 2024 Keywords: Solar tracking, Dual-axis, Artificial neural networks, Sliding mode control, Renewable energy. | This research presents a hybrid control technique for high-precision dual-axis solar tracking in photovoltaic systems, combining sliding mode control (SMC) with artificial neural networks (ANNs). An ANN model predicts the sun's altitude and azimuth angles based on time and date information. These predicted angles serve as reference inputs to an SMC algorithm that governs the rotational speeds of two DC motors adjusting the solar tracker's altitude and azimuth orientations. The SMC ensures robust tracking by calculating control signals that drive the DC motors to accurately follow the sun's trajectory, while leveraging the ANN's predictive capabilities. The proposed ANN-SMC approach mitigates uncertainties, rejects disturbances, and accounts for system nonlinearities, enabling optimal solar energy harvesting. Simulation results demonstrate the strategy's effectiveness, achieving highly accurate sun tracking with a mean absolute error below 0.09° for altitude and 0.27° for azimuth angles. This integration of neural networks and sliding mode control yields an efficient solar tracking system that maximizes energy yield. |

1. INTRODUCTION

Recent years have witnessed tremendous advancements in research and development for renewable energy systems such as solar, wind, and sea wave. Solar energy is the most dependable, continuously available, and ecologically benign renewable energy source among them. It is in a prime position to satisfy the high and rising global demand for energy. A solar photovoltaic (PV) system's output power is directly proportional to the amount of solar energy it receives. Nonetheless, the output power provided

ISSN: 1112-2242 / EISSN: 2716-8247



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by stationary solar PV systems is decreased due to the sun's constant movement in relative position. Solar tracking devices are seen to be the greatest substitute approach to deal with this problem (Fahad et al., 2019) (Al Nabulsi et al., 2010).

Solar trackers are categorized as single-axis or dual-axis based on their mechanical characteristics (Wu et al., 2016). Dual-axis trackers are favored for most concentrated solar technologies, except troughstyle systems, as they can optimally track the sun's position by rotating on two axes. In contrast, singleaxis (uniaxial) trackers have limited rotational capability, preventing optimal solar incidence and resulting in significant losses of potential energy from the PV modules. (Saeedi et al., 2021).To harness solar energy effectively, researchers have developed various sun-tracking methodologies, ranging from astronomical algorithms to optical sensing and intelligent controls, enabling efficient solar tracking for both single- and dual-axis systems.

For efficient sun-tracking in solar photovoltaic systems, we provide a hybrid control approach in this research that blends sliding mode control and neural networks. A neural network model is developed to predict the sun's altitude and azimuth angles based on time and date. These predicted angles serve as the reference inputs for a sliding mode controller that governs the positioning of the solar tracker's dual-axis mechanism.

2. SOLAR TRACKER CONTROL DESIGN

2.1. Solar Trajectory

The sun's path across the celestial sphere is characterized by two angular measurements - the altitude angle and the azimuth angle. These two angles form the foundation of the ecliptic coordinate system, which employs three coordinates (x', y', z') to specify positions. The sun's angular position within this system is denoted by the ecliptic longitude, a value that cycles from 0° to 360° over the course of the sun's full revolution. By utilizing the hour angle ω , the latitude ϕ of the observer's location, and the declination angle δ (the angle between the celestial equator and the sun's position), one can calculate the altitude angle α s and the azimuth angle γ s through the following trigonometric relationships:

$$\alpha_s = \sin^{-1} (\cos(\delta) \cos(\varphi) \cos(\omega) + \sin(\varphi) \sin(\delta))$$
(1)

$$\gamma_{s} = \cos^{-1}\left(\frac{\sin(\delta)\sin(\varphi) - \cos(\delta)\cos(\varphi)\cos(\omega)}{\cos(\alpha_{s})}\right)$$
(2)
$$\gamma_{s} = \gamma_{c} \qquad if \ \omega < 0$$

$$\gamma_s = 360^\circ - \gamma_c \qquad if \ \omega > 0 \tag{3}$$

$$\delta = 23.45 \sin\left[360^{\circ} \left(\frac{284+n}{365}\right)\right] \tag{4}$$

2.2 Motor Model

With voltage as the input and angle as the output, two DC motors—one for each axis of rotation powered the solar tracking system for the photovoltaic (PV) panels. While the second DC motor controlled the azimuth angle, which rotated the panel to track the sun's horizontal position, the first DC motor controlled the altitude angle, moving the PV panel to follow the sun's elevation in the sky. The relationship between the input voltage, the resultant torque, and the angular motion of the motor shaft can be represented by a set of equations that characterize the dynamic behavior of these DC motors, which capture the electromechanical characteristics taking into consideration factors like inductance, resistance, and mechanical inertia (Murali et al., 2018).

$$u_a(t) = u_{La}(t) + u_{Ra}(t) + e(t)$$
(5)

$$J\frac{d\omega(t)}{dt} = C_m(t) - C_f(t) \tag{6}$$

$$u_a(t) = L_a \frac{di_a(t)}{dt} + R_a i_a(t) + e(t)$$
⁽⁷⁾

$$J\frac{d\omega(t)}{dt} = K_c i_a(t) - f\omega(t)$$
(8)

| Parameter | Value |
|-----------|--------|
| R | 0.4 |
| L | 2.7 |
| J | 0.0004 |
| Kb | 0.0022 |
| Kt | 0.015 |
| Ке | 0.05 |
| | |

Table 1. Dc Motor Parameter

3. PROPOSED ANN-SMC

3.1. ANN Control

The artificial neural network (ANN) predictor, uses a synthetic neural network to determine the azimuth and elevation angles of the heliostat. The ANN takes three input parameters: the date and time, along with historical data on the heliostat's previous azimuth and elevation angles (Ikhwan et al., 2018).. By processing these inputs through its interconnected layers of artificial neurons, the ANN can learn to predict the optimal azimuth and elevation angles for accurately positioning the heliostat to track the sun's movement across the sky. This ANN-based approach leverages the ability of neural networks to discern complex patterns and relationships within the input data, enabling precise heliostat angle predictions without the need for explicit mathematical models or complex calculations. The neural network controller's generalized model is represented by:

$$u_i = f\left(\sum_{j=1}^n w_j \, x_i + \theta\right) \tag{9}$$

where $f(\cdot)$ is a nonlinear activation function, w_j connection signal weights, x_j input signals, θ as the bias and j=1,2,...,n with n as the count of inputs, and to learn more about its formulation, consult (Zeghoudi et al., 2023).

3.2. Sliding Mode Control

The reaching mode and the sliding mode make up the control signal in the Sliding Mode Control (SMC) technique. A switching control (usw) is used in the reaching mode to move the system's state trajectory onto a predefined sliding surface. An equivalent control (ueq) keeps the system stable by keeping it on the sliding surface once it enters the sliding mode state. Equation (10), which represents the whole sliding mode control signal, can be represented. This control approach is illustrated by the SMC diagram, which shows the control signal as the result of combining the switching control and comparable control components. The system's convergence to the sliding surface and subsequent stable tracking along it are guaranteed by this dual-mode control strategy (Palomino et al., 2023).

$$\mathbf{u}_{\rm smc}(\mathbf{t}) = \mathbf{u}_{\rm eq} + \mathbf{u}_{\rm sw} \tag{10}$$

$$u_{sw} = Ksgn(s) \tag{11}$$

The trajectory converges to the sliding surface more quickly the bigger the value of K, provided that K > 0 is chosen to be suitably large.

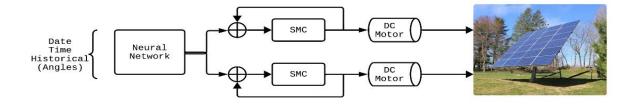


Fig 1. Block schematic of the suggested tracking system for ANN-SMC.

The proposed approach (Fig.1) combines sliding mode control with a neural network model for suntracking in solar PV systems. The neural network predicts sun angles based on time/date as reference inputs. The sliding mode controller regulates motor speeds to adjust tracker orientation following sun trajectory. This hybrid strategy leverages robustness of sliding mode control and predictive capability of neural networks for maximizing energy harvesting.

4. RESULTS AND DISCUSSIONS

As seen in Figures, the simulation results utilizing artificial neural network (ANN) controllers were able to follow the intended altitude reference value with exceptional accuracy. Furthermore, the azimuth tracking performed really well. In order to evaluate the accuracy of the azimuth and altitude angles, the error values for azimuth and altitude may be seen following the application of sliding mode control (SMC) and ANN prediction for DC motor control, as shown in the following picture.

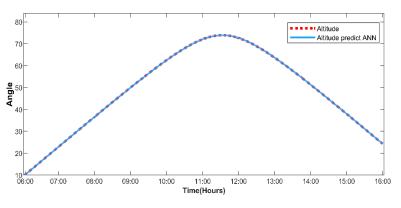


Fig 2. Comparison between predict ANN and reference Altitude.

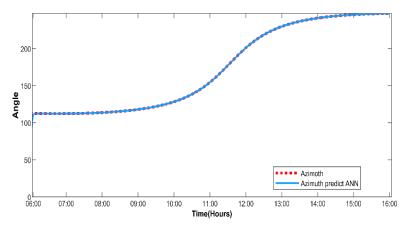


Fig 3. Comparison between predict ANN and reference Azimuth.

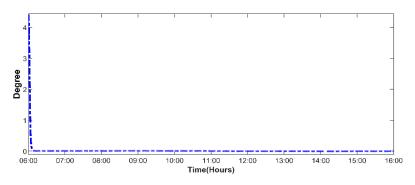


Fig 4. Error in Altitude Tracking After ANN Prediction and SMC Control.

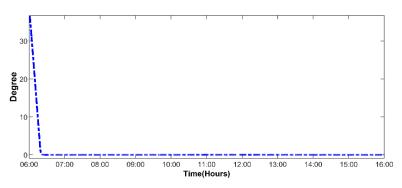


Fig 5. Error in Azimuth Tracking After ANN Prediction and SMC Control.

The extremely precise tracking capability attained is demonstrated in Figure 4, where the mean absolute error (MAE) of just 0.089 degrees is an astoundingly low error number. Further insights are provided by Figure 5, which shows that even while azimuth tracking errors were higher than those related to altitude tracking, the error rate remained within a good limit, with an MAE of 0.27 degrees.

5. CONCLUSION

This research presents a novel hybrid control technique for high-precision dual-axis sun tracking in photovoltaic systems, integrating SMC and artificial neural networks (ANNs). Based on time and date data, an ANN model forecasts the sun's azimuth angles and altitude. The two DC motors that rotate at different speeds to change the orientation of the solar tracker are driven by an SMC algorithm, which uses these anticipated angles as reference inputs. By utilizing the ANN's predictive powers, the SMC generates control signals that precisely guide the motors to monitor the sun's path, ensuring reliable tracking.

The efficiency of the suggested ANN-SMC strategy was shown by the simulation results, which produced extremely accurate sun tracking with a mean absolute error of less than 0.09° for altitude and 0.27° for azimuth angles. The synergistic integration of neural networks and sliding mode control techniques yields an efficient and responsive solar tracking system that maximizes energy yield from photovoltaic installations. This strategy mitigates uncertainties, rejects disturbances, and accounts for system nonlinearities, enabling optimal solar energy harvesting and contributing to sustainable renewable energy production.

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