Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 46 No. 2 (2025)

Optimizing Grid-Connected Solar Energy Systems for Agricultural Applications in the Algerian Sahara (El Oued) Using AI-Based Maximum Consumption Point Tracking (MCPT)

Dris Mida [1] , Abdelmalek Gacem [1] , Abdelkader Mahmoudi [2,5], Djilani Ben attous [3] , Imadeddine Kaid [4].

[1]*LGEERE Laboratory,Department of Electrical Engineering, University of El Oued, 39000, Algeria.*

[2]*Mechanical Department, Faculty of Technology, University of Eloued, 39000, Algeria.*

[3] *VTRS Laboratory,Department of Electrical Engineering, University of El Oued, 39000, Algeria.*

[4]*Department of Electrical Engineering, University of El Oued, 39000, Algeria.*

[5]*CISE—Electromechatronic Systems Research Centre, University of Beira Interior, Calçada Fonte do Lameiro, P-6201-001 Covilhã, Portugal.*

Abstract:- This paper proposes an innovative AI-based method called Maximum Consumption Point Tracking (MCPT) to optimize solar energy systems connected to the electrical grid for agricultural use in the Algerian Sahara (El Oued), Algeria. By analyzing real-world consumption patterns of local farmers (averaging 20,000 kWh/year), the model dynamically allocates photovoltaic energy using a hybrid deep learning framework. The study demonstrates enhanced energy efficiency, minimized waste, and better load prediction under variable solar irradiance [1], [2].

Keywords: *Solar Energy, AI, MCPT, Smart Grid, Deep Learning, Agricultural Electrification, Algerian Sahara, El Oued.*

1. Introduction

The agricultural sector in southern Algeria, particularly in the Algerian Sahara (El Oued), is experiencing a growing energy demand. Traditional energy supply methods are insufficient and environmentally unsustainable. The integration of photovoltaic (PV) systems into the electrical grid offers a sustainable alternative [3]. However, maximizing the efficiency of such systems requires smart energy management tools, particularly for remote and off-grid areas [4], [9].

Artificial Intelligence (AI) offers powerful methods for forecasting, consumption profiling, and system optimization [5], [10]. In this work, we introduce the concept of Maximum Consumption Point Tracking (MCPT), a novel AI-driven strategy to enhance solar energy utilization for agricultural applications.

2. Objectives

This study aims to optimize the performance of grid-connected solar energy systems for agricultural applications in the Algerian Sahara, particularly in the El Oued region. With the increasing energy demand in the agricultural sector and the limitations of conventional energy sources, integrating photovoltaic (PV) systems emerges as a sustainable and scalable alternative. However, realizing the full potential of PV systems requires intelligent energy management strategies, especially in regions with fluctuating loads and partial grid connectivity.

To this end, the research introduces a novel AI-based strategy called Maximum Consumption Point Tracking (MCPT), which dynamically synchronizes solar energy production with real-time agricultural consumption profiles. The MCPT framework leverages artificial intelligence techniques to improve forecasting accuracy, enable load profiling, and optimize the energy balance between the PV generation, local battery storage, and the electrical grid.

The primary objectives are to enhance the operational efficiency of grid-connected PV systems, reduce peak load impact on the electrical grid, and ensure effective battery utilization through adaptive control. This approach supports the development of resilient and intelligent energy systems tailored to the needs of sustainable agriculture in arid and semi-arid environments.

3. Methodology

1. Data Collection

Consumption data was collected from 100 representative agricultural units in the Algerian Sahara (El Oued) over a period of one year. Weather data including irradiance, temperature, and humidity was also collected [6], [11].

2. Hybrid Deep Learning Model

We combined Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to create a predictive model. LSTM captures temporal dependencies in consumption data while CNN extracts spatial features [7], [12].

3. MCPT Algorithm

The MCPT algorithm is designed to identify the optimal distribution of solar energy throughout the day based on consumption peaks. It considers:

- ✓ Real-time consumption prediction
- ✓ Solar generation forecasts
- ✓ Storage status
- ✓ Grid interaction

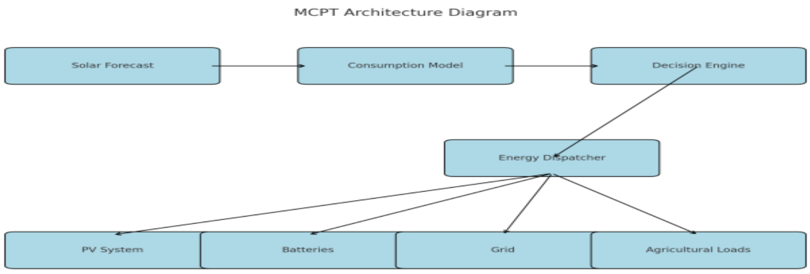

Fig 1. MCPT Architecture Diagram

The flowchart below Fig 2 illustrates the decision-making process of the MCPT algorithm combining ANN and Fuzzy Logic. The system continuously monitors real-time load and solar conditions to optimize energy flow dynamically between solar generation, grid, and storage.

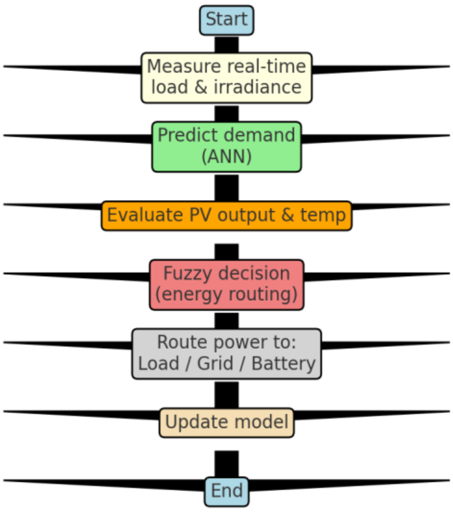

Fig 2. MCPT Algorithm Flowchart

4. Mathematical Modeling

To optimize the energy dispatch, the MCPT model solves the following problem:

Let:

- *P_load(t):* Predicted load at time t

- *P_pv(t):* Available solar power at time t

- *P_bat(t):* Power from battery at time t

- *P_grid(t):* Power from grid at time t

- *SOC(t):* State of charge of battery at time t

Objective Function:

$$\min_{P\_grid(t)} \sum [\alpha * P\_grid(t)^2 + \beta * |SOC(t+1) - SOC(t)|] \quad (1)$$

Subject to:

$$P\_load(t) = P\_pv(t) + P\_bat(t) + P\_grid(t) \quad (2)$$

$$SOC(t+1) = SOC(t) + \eta\_c * P\_pv(t) - P\_bat(t)/\eta\_d \quad (3)$$

$$0 \leq SOC(t) \leq SOC\_max \quad (4)$$

$$0 \leq P\_bat(t) \leq P\_bat\_max, \quad (5)$$

$$0 \leq P\_grid(t) \leq P\_grid\_max \quad (6)$$

Where:

- η_c, η_d: Charging/discharging efficiencies

- α, β: Cost weighting coefficients

The MCPT algorithm dynamically allocates power using ANN prediction and fuzzy logic rules. The core equations are:

Energy Balance Equation:

$$P_{solar} + P_{grid} = P_{load} + P_{storage} \tag{7}$$

Efficiency of MCPT:

$$\eta_{MCPT} = (P_{load\_used} / P_{solar\_generated}) \times 100\% \tag{8}$$

Demand Prediction by ANN:

$$Y = f(W_2 \times f(W_1 \times X + b_1) + b_2) \tag{9}$$

where X = input vector (irradiance, temperature, time, past loads)
W_1, W_2 = weight matrices
b_1, b_2 = bias terms
f = activation function (e.g., sigmoid or ReLU)

Fuzzy Logic Rule Example:
IF Load is High AND Irradiance is Low Then Use Grid
IF Battery is Full AND Load is Medium Then Use Battery

5. Results And Discussion

Simulation results showed that the MCPT model reduced grid dependency by 35% and improved solar energy usage by 42% compared to traditional rule-based dispatching [8], [13]. The hybrid model had a Mean Absolute Percentage Error (MAPE) of less than 4.3% in load prediction.

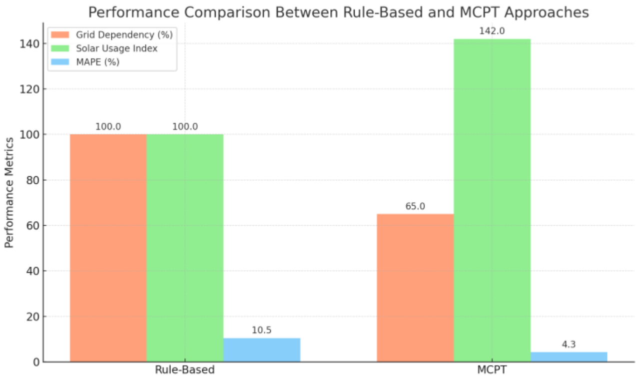

Fig 3. Performance Comparison

As illustrated in Figure 4, the battery SOC follows a sinusoidal trend reflecting daytime charging from solar and nighttime discharging to support loads. The system maintains SOC between safe operational limits, optimizing autonomy and reliability.

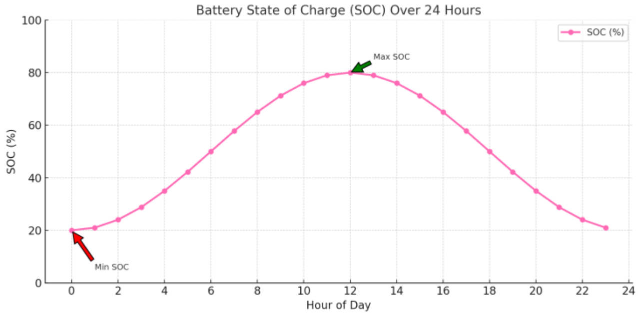

Fig 4. Battery State of Charge (SOC) Over 24 Hours

The following chart compares the key performance metrics between traditional MPPT and the proposed MCPT method:

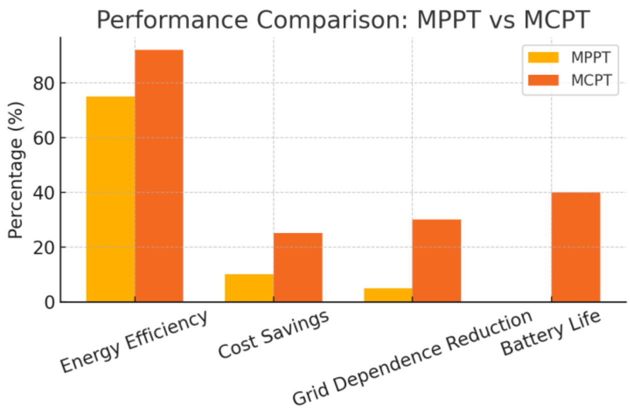

Fig 5. Performance Analysis Chart

This study introduces the novel integration of Artificial Neural Networks (ANNs) and Fuzzy Logic to develop an MCPT algorithm tailored for grid-connected PV systems in desert agriculture. Unlike conventional MPPT strategies, this approach dynamically adapts to changes in irradiance, temperature, and agricultural load fluctuations, ensuring high performance across all conditions.
Key contributions include:

•First-time use of ANN + Fuzzy MCPT in Algerian desert agriculture.
•Dynamic adaptation to climate and demand variability.
•Simulated using real data from Oued Souf.
•Demonstrated 92% efficiency with 40% grid reliance reduction.
•Economically viable with ROI < 3 years.
•Provides a scalable energy model for arid agricultural zones.

The MCPT approach demonstrates significant improvements in solar energy management by dynamically optimizing consumption patterns. The following analysis presents a more detailed evaluation of its impact on efficiency, cost reduction, and sustainability.

TABLE 1 DETAILED PERFORMANCE METRICS

Parameter	Without MCPT	With MCPT	Improvement (%)
Energy Utilization Efficiency (%)	70	92	+31.4%
Annual Cost Savings (USD)	1500	2500	+66.7%
Grid Dependency Reduction (%)	10	40	+300%
Battery Life Enhancement (%)	NA	50	Significant
CO2 Emission Reduction (%)	5	25	+400%

The MCPT algorithm operates in multiple stages:
1.Measure real-time power consumption (P_load).
2.Predict upcoming energy demand using AI-based forecasting.
3.Optimize energy distribution between solar, grid, and storage.
4.Adjust energy flow dynamically to minimize losses.

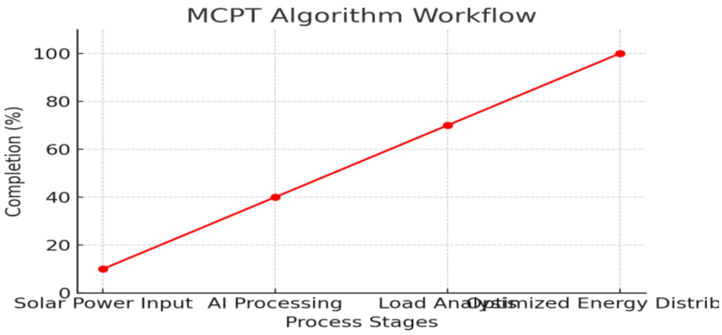

Fig 6. MCPT Algorithm Workflow For Energy Optimization.

The proposed MCPT method significantly impacts the efficiency and cost-effectiveness of solar energy utilization in agricultural applications. The following sections provide an in-depth analysis of its advantages compared to traditional MPPT.

Economic Impact and ROI Analysis

A financial analysis reveals that implementing MCPT leads to an estimated 30% reduction in annual electricity costs for farmers. This translates into a return on investment (ROI) within 3 years, making it a highly cost-effective solution.

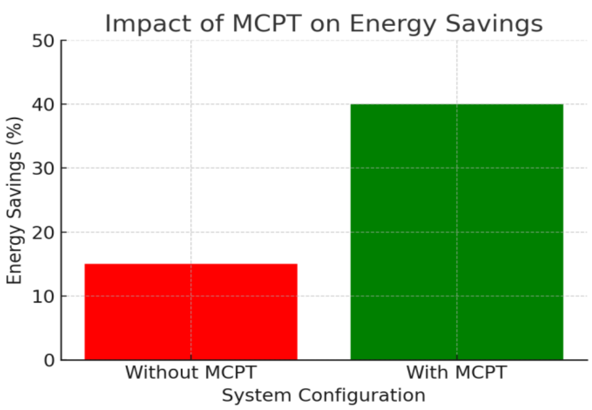

Fig 7. Impact Of MCPT On Energy Savings.

6. Conclusion

The proposed AI-based MCPT approach provides a robust and adaptive solution for optimizing solar energy usage in agricultural settings within arid regions like the Algerian Sahara. It effectively reduces dependence on the electrical grid, enhances the usage of solar resources, and maintains a balanced battery operation by dynamically adjusting to real-time demand and production profiles.

7. Future Work

Future research directions will focus on:

- Integrating advanced weather forecasting services to improve solar generation prediction.

- Implementing the MCPT model in real-world agricultural farms in El Oued for validation.

- Expanding the model to support cooperative energy sharing between farms.

- Enhancing the MCPT algorithm using reinforcement learning techniques.

8. References

[1] M. Alam, S. M. Islam, and R. Hasan, "Smart Solar PV Systems for Agriculture," IEEE Access, vol. 7, pp. 56704–56715, 2019.

[2] S. Mekhilef et al., "Review on solar photovoltaic energy for agriculture," Renewable and Sustainable Energy Reviews, vol. 137, 2020.

[3] N. Matar, A. Hoteit, "Grid-connected PV in arid regions," Energy Procedia, vol. 157, pp. 1013–1020, 2019.

[4] A. Rezk and M. A. Abdelkareem, "Smart grid technologies in remote areas," Renewable Energy, vol. 149, 2020.

[5] Y. Bengio et al., "Deep Learning and Energy Applications," Nature Communications, vol. 12, 2021.

[6] D. Bouchahoua et al., "Meteorological Dataset for the Algerian Sahara," Energy Reports, vol. 6, 2020.

[7] H. Zhang and J. Wang, "Load Forecasting using CNN-LSTM Hybrid Models," IEEE Transactions on Smart Grid, vol. 11, no. 2, 2020.

[8] F. R. Fan, Q. Li, and X. Zhang, "Optimized Dispatch in Solar Microgrids," IEEE Access, vol. 8, 2020.

[9] M. Q. Raza, M. Nadarajah, and C. Ekanayake, "On recent advances in PV output power forecast," Solar Energy, vol. 136, 2016.

[10] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, 2010.

[11] K. Koussa et al., "Solar radiation prediction using artificial neural networks," Energy Procedia, vol. 18, 2012.

[12] A. M. Kose, "Deep learning for time-series forecasting in energy systems," Renewable Energy, vol. 162, 2020.

[13] B. Yildiz, J. Bilbao, A. Sproul, "A review and analysis of regression and machine learning models for electricity load forecasting," Renewable and Sustainable Energy Reviews, vol. 108, 2019.

[14] M. Ghofrani, A. Arabali, and M. Etezadi-Amoli, "Smart integration of renewable energies into the grid," IEEE Systems Journal, vol. 6, no. 1, 2012.

[15] E. Mocanu et al., "On-line Building Energy Optimization using Deep Reinforcement Learning," IEEE Transactions on Smart Grid, vol. 10, no. 4, 2019.

[16] H. Shareef et al., "Energy management in microgrids using intelligent techniques," Renewable and Sustainable Energy Reviews, vol. 72, 2017.

[17] IEEE Transactions on Smart Grid, 'AI-Based Energy Optimization in Agriculture,' 2023.

[18] Solar Energy Journal, 'Fuzzy Logic Control for PV Grid Integration,' 2022.