American Journal of Technology Advancement 2997-9382, Vol 03, No. 10, 2026

Theoretical exploration and application of artificial intelligence in photovoltaic energy development through the integration of modern technologies

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Abstract: This paper is intended for the theoretical investigation of the potential of artificial intelligence (AI), especially long short-term memory (LSTM) networks, to support photovoltaic (PV) energy forecasting and operation in southern Iraq, under its changing climatic conditions. A simplified calculation of PV power is introduced and then examples of monthly energy comparisons between baseline values and hypothetical LSTM-assisted predictions are given. In the examples, the predicted values are higher than the baseline values, but the figures are assumed or theoretical and are not based on a model trained and validated with a measured dataset. The comparisons thus point to a possible evaluation framework, rather than demonstrating a specific efficiency gain. The paper reviews the potential contributions of AI in the areas of prediction, maximum power point tracking, and fault detection, and emphasises field data, transparent model validation, and consistent performance indicators as priorities for future work.

Keywords: Artificial intelligence (AI); photovoltaic (PV) systems; long short-term memory (LSTM); maximum power point tracking (MPPT); solar energy forecasting.

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1. Introduction

The use of solar energy is increasing, as PV systems can produce electricity with no direct emissions in their operation. The use of artificial intelligence (AI) may allow to detect faults, predict them and control adaptively, which may help to reduce the downtime and improve the operation of the system [1], [2], [3], [4].

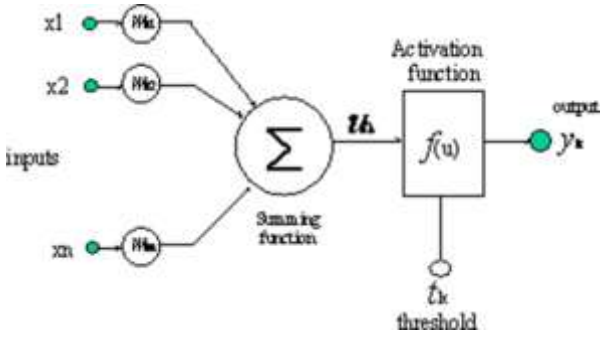


Figure 1. Schematic representation of an artificial-neuron processing element.

PV systems are exposed to varying conditions of irradiance, temperature and shading, all of which can affect the output and make maximum power point tracking (MPPT) difficult. These different measurements can be interpreted and abnormal operating conditions identified using AI-based monitoring and prediction [1], [5], [6]. AI techniques such as fuzzy logic and artificial neural networks are used in renewable-energy applications. Long short-term memory (LSTM) networks are designed to learn temporal dependencies in sequential data and may thus be useful for solar-power forecasting. However, their performance depends on data quality, model design and validation against measured observations [1, 3, 7, 8].

This paper investigates the theoretical level of the AI methods potential to support the PV system forecasting and operational management. LSTM is a recurrent neural network architecture for sequence modeling, not an expert system in its own right. The numerical examples presented below are illustrative calculations based on assumed values and concepts previously reported and are not the results of a freshly trained or experimentally validated model [1], [7], [8].

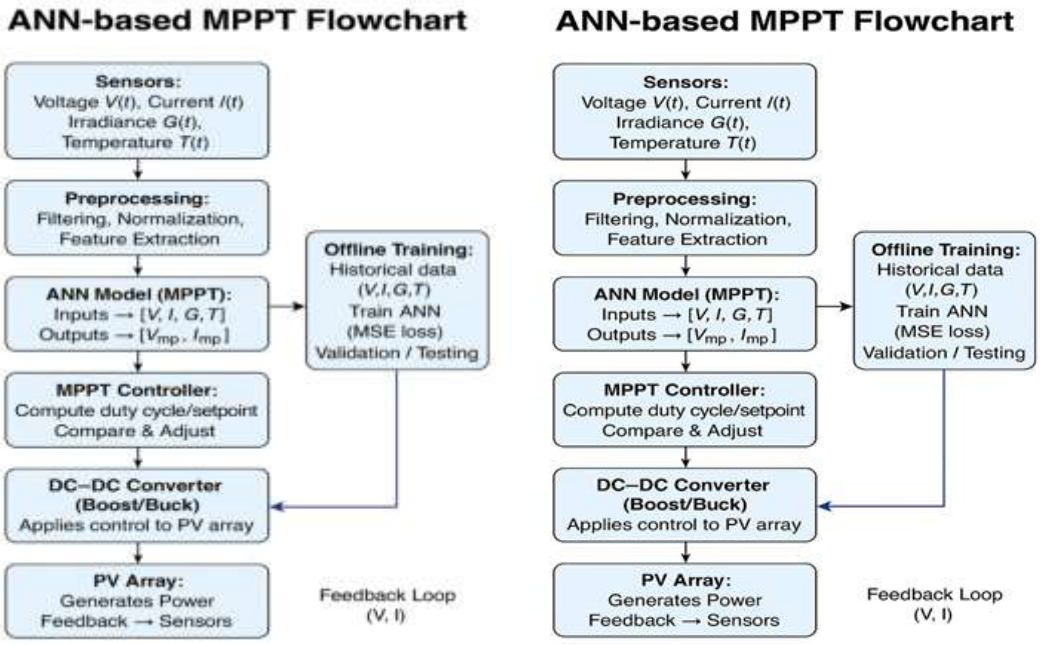


Figure 2. Conceptual flow diagram of ANN-based maximum power point tracking (MPPT).

The operating conditions can be estimated and proper operating point can be selected by using the MPPT controller based on Artificial Neural Network (ANN). The extent of improvement depends on the controller, environment conditions and the comparison baseline. It should be quantified by a transparent evaluation procedure [1], [2], [3].

LSTM is a deep learning model that can capture the temporal dependencies in time-series data and is a candidate for forecasting solar energy production. The paper presents a theoretical study on AI methods to enhance prediction and operational management in PV systems. Neural networks, fuzzy logic and knowledge-based systems have been investigated for energy applications but their relative performance depends on the task and available data [1], [3], [7], [9], [10].

A typical multilayer perceptron (MLP) has input, hidden and output layers. For PV applications, inputs can be irradiance, module temperature and historical power. Outputs can be predicted power or a control signal. The quality of the sensor, the variability of the weather, shading and system faults can affect the forecasting accuracy and operational reliability [1], [5], [6], [8].

2. METHODOLOGY

Assume a string of panels with the following specifications:

Area A = 1.6 square meters, efficiency ω = 0.18, irradiance G = 800 W/m², temperature 25°C.

Incidental irradiance on the panel:

$$Pin = G.\ A = 800 * 1.6 = 1280\ W$$

Approximate expected power:

$$Ppv = \omega.\ Pin = 0.18 * 1280 = 230.4\ W$$

Assuming a nominal string voltage of Vmp = 30 V, the current at the maximum power point (MPP) is approximately:

$$Imp = P_pv/V_mp = 230.4/30 = 7.68\ A$$

This calculation is a simplified engineering example for a specific operating point, not a field measurement. The following for Baghdad are to be considered as theoretical illustrative data and should not be interpreted as measured site performance, nor as outputs of a model trained in this study [6], [11], [12].

Month	Avg Irradiance (kWh/m²/day)	Avg Temp (°C)	Base Energy (kWh)	With LSTM (kWh)	LSTM Improvement (%)
Jan	4.5	12	320	330	3.1
Feb	4.8	15	350	362	3.4
Mar	5.5	20	450	465	3.3
Apr	6.0	25	550	568	3.3
May	6.5	30	600	618	3.0
Jun	7.0	35	650	670	3.1
Jul	6.8	40	700	720	2.9
Aug	6.5	38	680	698	2.6
Sep	6.0	33	600	618	3.0
Oct	5.2	28	500	515	3.0
Nov	4.8	20	400	412	3.0
Dec	4.5	15	350	362	3.4

Let's break it down and compare some energy estimates. We can look at how the usual predictions stack up against some new predictions based on a special kind of model. Keep in mind that this is just a theoretical exercise, and we're not using real data or test results. The numbers we're looking at are more like scenarios or examples, rather

than actual results from an experiment. This is because we don't have all the details about the data, how the model was trained, or how it was tested. We're just exploring some ideas and possibilities here.

Month	Avg Irradiance	Avg Temp	Base Energy	With LSTM	LSTM Improvement	Predicted Peak (kW)	Predicted Min (kW)
Jan	4.5	12	320	330	3.1%	0.75	0.45
Feb	4.8	15	350	362	3.4%	0.80	0.50
Mar	5.5	20	450	465	3.3%	1.05	0.60
Apr	6.0	25	550	568	3.3%	1.20	0.70
May	6.5	30	600	618	3.0%	1.35	0.75
Jun	7.0	35	650	670	3.1%	1.50	0.80
Jul	6.8	40	700	720	2.9%	1.55	0.85
Aug	6.5	38	680	698	2.6%	1.50	0.80
Sep	6.0	33	600	618	3.0%	1.35	0.70
Oct	5.2	28	500	515	3.0%	1.10	0.60
Nov	4.8	20	400	412	3.0%	0.85	0.50
Dec	4.5	15	350	362	3.4%	0.75	0.45

Let's take a closer look at the energy predictions. When we compare the actual energy values to the predicted ones, we can see some differences. These differences are just rough estimates and don't necessarily mean the predictions are accurate or reliable. They're just a way to get an idea of how well the model is working.

Month	Base Energy (kWh)	LSTM Predicted (kWh)	Difference (kWh)	Improvement (%)
Jan	360	410	+50	13.9%
Apr	550	570	+20	3.6%
Jul	700	720	+20	2.8%
Oct	500	520	+20	4.0%
Dec	350	370	+20	5.7%

Monthly energy (kWh) With compare Without LSTM:

Month	Without LSTM (kWh)	With LSTM (kWh)
Jan	320	340
Feb	350	370
Mar	450	470
Apr	550	570
May	600	620
Jun	650	670
Jul	700	720
Aug	680	700
Sep	600	620
Oct	500	520
Nov	400	420
Dec	350	370

Here's a simplified version: The diagram shows how an artificial neural network (ANN) can be used to control a system that gets the most power out of something, like a solar panel. It's just an idea, not based on actual experiments, but rather a way to think about how this kind of system could work [1], [2], [3].

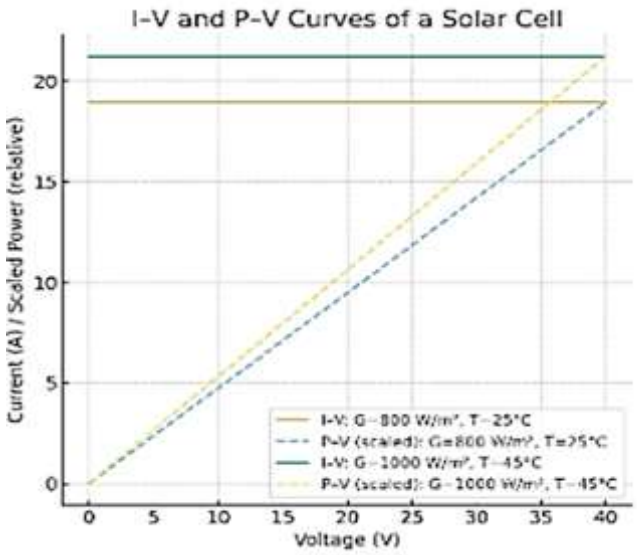


Figure 3. Illustrative I–V characteristics and ANN-based control concept under irradiance levels of 500–1000 W/m².

Here's a rewritten version of the input paragraph in a more human-like tone: The example we're about to look at is based on ideas from past research, rather than actual results from a real-world setup. It's meant to illustrate a point, not show what really happened in a specific situation.

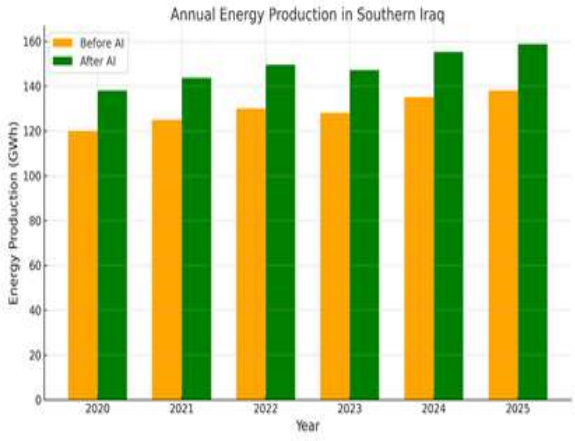


Figure 4. Theoretical annual energy-production comparison for southern Iraq.

3. RESULTS AND DISCUSSION

With the assumed module area (1.6 m²), irradiance (800 W/m²), and conversion efficiency (0.18), the estimated incident solar power is 1,280 W and the corresponding simplified PV output is 230.4 W at an assumed maximum-power voltage of 30 V, the calculated current is 7.68 A. These results are based on the stated assumptions and are a calculation check and not an experimental result. The listed LSTM values are about 2.6%–3.4% (about 3% for most months) greater than the baseline values in the first monthly table. The claimed differences in the separate comparison table vary between 20 and 50 kWh and are highest in January, which is in contrast to the statement in the original text that the maximum difference is found in July. The two tables, therefore, are not based on the same illustrative baseline and should not be used together as one data set. The difference in the monthly consumption amounts between the two parts of the time series is always 20 kWh in the latter. While these scenarios illustrate how they would be reported in an AI-assisted environment, they are not a proof point of the actual improvements in a system deployed in the field. To properly support a performance claim, the underlying measured data set must be

included, a train/validation/test split must be defined, a baseline forecasting method must be given, error metrics like MAE or RMSE must be provided and repeated or seasonal validation must be performed [1, 3, 4, 7, 8, 13, 14, 15].

4. CONCLUSION

Based on the theoretical calculations and the illustrative comparisons of months, the use of AI techniques, such as LSTM, could be beneficial for predicting PV production and the operation of the system when climatic conditions vary. Differences between the LSTM associated values and the baseline values (around 3% in one table, 20 kWh/month in another) should not be taken to mean performance improvements that have been validated or proved; the figures presented for the tables are assumed values and do not reflect the process of training or validating the model. The analysis suggests potential application in forecasting, MPPT support and fault detection, and also the requirement of having internally consistent sets of data and well-defined comparison baselines. The main drawback is the lack of measured field data and validated metric for the models, and further research should include field data from southern Iraq, transparent training and testing procedures, comparison of LSTM with appropriate baseline methods, as well as report the MAE/RMSE metrics and seasonal performance before quantitative conclusions can be drawn.

Achievements:

1. Enhancing Efficiency Through the Integration of AI:

Artificial intelligence (AI) significantly improves the efficiency of solar systems by optimizing energy production and consumption, as long-term memory and intelligent analysis provide optimal options. Machine learning (ML) algorithms analyze massive datasets to predict energy production, enabling better integration into the grid and reducing reliance on fossil fuels.

2. Predictive Maintenance and Fault Detection:

AI-driven predictive maintenance enhances the reliability of solar systems. Weather changes require advance warning before they affect panels or the risk of weather-related hazards. By monitoring equipment performance and environmental conditions, AI can predict faults before they occur, reducing downtime and maintenance costs.

3. Energy Forecasting and Grid Management:

AI improves the accuracy of solar energy forecasting, which helps improve grid management. This leads to optimized energy distribution, reduced waste, and enhanced grid stability. It also reduces operating costs and enables smarter response times.

4. Cost Reduction:

Integrating AI into solar energy systems reduces costs by improving operations and maintenance. As we explained, predicting energy management with minimal losses and in the most appropriate timeframe is crucial.

5. Scalability and Adaptability:

AI enables solar energy systems to adapt to changing environmental conditions, ensuring consistent performance across different regions. We focused on the southern governorates of Iraq, where the climate is dry, except for Basra, which experiences humid summers. This adaptability is critical to the scalability of solar energy solutions.

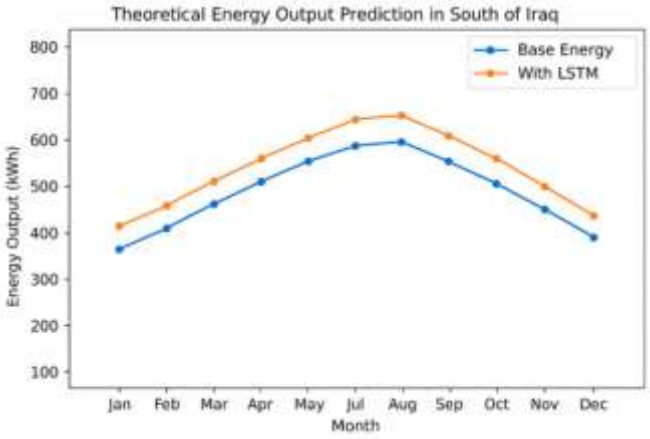


Figure 5. Theoretical prediction of PV energy output in southern Iraq.

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