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Original Research Article

A Multi-Resolution Approach Based on the Integration of a Nonlinear Physical Model and Long Short-Term Memory Network for Photovoltaic Power Modeling and Forecasting

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ABSTRACT

In the current context of energy transition, accurately forecasting solar power production is a major challenge for the efficient operation of electricity grids that include renewable energy sources. This work aims to improve prediction performance by combining a nonlinear physical model based on the principles of photovoltaic conversion with a recurrent neural network designed for time series analysis. The underlying hypothesis is that integrating physical knowledge with data-driven learning can better capture the complexity of solar energy patterns. The proposed method involves careful selection of input variables through correlation analysis and embedding the physical model within a deep learning structure. Results, evaluated using standard error metrics, demonstrate a clear improvement in forecasting accuracy compared to conventional approaches. While the physical model considered on its own produces a high error level (root mean square error = 338.55 and mean absolute error = 182.08), methods based on artificial intelligence significantly reduce these values (long short-term memory network: root mean square error = 3.29; recurrent neural network: 2.87). The hybrid method developed in this study achieves the best overall performance (root mean square error = 2.83 and mean absolute error = 1.26). This study contributes to the development of more reliable prediction systems capable of anticipating fluctuations in solar power generation due to changing environmental conditions.

KEYWORDS

Photovoltaic power prediction, Solar power prediction, Hybrid modeling approach, LSTM neural networks, Nonlinear physical models, Time series forecasting.

INTRODUCTION

In a world undergoing an energy transition, the integration of renewable energies has become a priority. It is shown in [1] that photovoltaic (PV) solar energy is one of the most promising renewable sources, while [2] highlights recent technological improvements in PV systems. Furthermore, [3] stresses that renewable energy adoption is essential for meeting today's environmental challenges, and [4] demonstrates that large-scale PV deployment offers significant economic advantages.

The rapid global growth of solar installations has increased the need for accurate forecasting. In [5] Z. Garip *et al.* examined the expanding use of forecasting in solar energy systems, and [6] shows that forecast accuracy directly impacts energy management. In addition, [7] proves that improved forecasting methods enhance grid operation. Recent global

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assessments, such as [8], confirm unprecedented increases in annual PV capacity additions. Similarly, [9] emphasizes that accurate power forecasting is crucial for maintaining grid stability as PV penetration rises.

However, predicting PV power remains challenging due to environmental variability. It is identified in [10] that irradiance fluctuations, cloud cover, and temperature as major uncertainties affecting PV output. Moreover, [3] explains that the physical processes governing PV production add further complexity.

To structure this research field, several reviews categorize the main forecasting approaches. The paper [4] provides a classification into physical models, statistical methods, and AI-based or hybrid models.

Physical models rely on meteorological variables and PV system characteristics. Y. Zhi *et al.* explain in [8] how atmospheric data drive physical simulations, while [11] evaluates the robustness and theoretical reliability of such models. Still, [5] notes that physical models require intensive calibration and may be computationally demanding, which limits their deployment.

Statistical models offer a simpler alternative. K. Kamberi *et al.* show in [3] that ARMA and SVR-based statistical methods can yield good results under stable weather but degrade when conditions shift rapidly.

Machine learning and deep learning approaches have shown stronger predictive capabilities. Tripathi *et al.* [7] presents early advances in ML-based solar forecasting, while [12] discusses contributions from deep learning architectures. In addition, [13] demonstrates that neural networks significantly improve prediction accuracy under diverse conditions, confirming observations in [9]. Long short-term memory (LSTM) networks, described in [14], are especially effective for time series because they capture long-term dependencies, a finding further supported by [15].

Nonetheless, deep learning models face certain limitations. H. Hafdaoui *et al.* highlight in [13] their limited interpretability, and Z. Garip in [5] reports reduced generalization when exposed to unfamiliar atmospheric conditions. To address these issues, hybrid approaches have emerged. So, [16] and [17] show that integrating physical knowledge into ML architectures increases robustness and accuracy. Moreover, [18] confirms that combining physically derived information with data-driven strategies improves short-term forecasting.

Hybrid approaches typically incorporate physically meaningful variables. U. Singh *et al.* propose in [19] integrating irradiance and temperature estimates into models, while [20] uses clear-sky indices and radiation transposition outputs as additional features. Furthermore, [21] shows that such physical features improve generalization under varying atmospheric conditions.

Several illustrative hybrid architectures have been proposed. So, [22] introduces a framework combining satellite imagery, NWP forecasts, and machine learning for intra-day irradiance prediction. Also, [21] presents a hybrid model merging CEEMDAN signal decomposition with CNN–LSTM networks to handle non-stationary conditions more effectively. Additionally, [4] discusses physics-informed neural networks that enforce physical constraints within learning processes.

More recently, [23] summarizes hybrid irradiance forecasting approaches combining satellite inputs, NWP models, and AI tools. A complementary study in [24] proposes a SARIMA–LSTM hybrid enhanced through STL decomposition using LOESS, demonstrating improved short-term solar radiation forecasting. In PV power prediction, [18], shows that decomposition-based hybrid models outperform standalone neural networks, especially during transitional weather periods.

Despite these advances, many hybrid architectures remain loosely coupled. In [25], it is noted that physical and AI models often operate in parallel rather than being deeply integrated. Consequently, [12] calls for unified frameworks embedding physical principles directly into neural network learning mechanisms.

To address this gap, the present work proposes a tightly integrated hybrid method combining a nonlinear physical model with an LSTM neural network. This idea aligns with insights from [26], which demonstrates that fusing physical forecasts with data-driven learning enhances both interpretability and accuracy. Building on this foundation, our approach aims to improve short-term PV power prediction under variable environmental conditions, consistent with findings reported in [27].

The rest of the paper is organized as follows: Section II presents the methodology, Section III describes implementation and results, and Section IV concludes the study.

MATERIALS AND METHODS

The data used come from sensors that record daily measurements [2] at regular one-minute intervals, Table 1.

Table 1. Dataset overview

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
01/01/2021 00:00	1.6727	-1.4862	118.65	-0.672869999999999	13.652	0.9666	-0.04227	0.008859999999999	0.00354	-1.7702	-3.5522	-3.5336	-3.2592	-2.6814	10
01/01/2021 00:01	1.6713	-1.4529	118.65	-0.73143	13.653	0.94264	-0.043549999999999	-0.443079999999999	0.0178	-1.7842	-3.6531	-3.499	-3.2125	-2.7644	10
01/01/2021 00:02	1.6719	-1.464	118.72	-0.79227	13.655	0.92725	-0.0441	-0.08418	0.004309999999999	-1.7876	-3.6049	-3.4852	-3.1522	-2.7367	10
01/01/2021 00:03	1.6719	-1.4307	118.84	-0.8224	13.654	0.90502	-0.050869999999999	-0.27914	0.025	-1.7785	-3.489	-3.4639	-3.1803	-2.8473	10

For clarity and consistency, Table 2 shows how each alphabetical column label (A–P) was converted to its corresponding variable name.

Table 2. Column label mapping

A	measured_on
B	ac_current__427
C	ac_power__423
D	ac_voltage__426
E	ambient_temp__428
F	das_battery_voltage__434
G	das_temp__433
H	dc_pos_current__425
I	dc_pos_voltage__424
J	dc_power__422
K	inverter_temp__432
L	module_temp_1__429
M	module_temp_2__430
N	module_temp_3__431
O	poa_irradiance__421
P	system_id

The dataset contains 15 data columns collected over a period of more than three years, including information on ambient temperature, panel temperature, irradiation, current intensity and voltage, as well as data related to the batteries and the inverter.

An exploratory data analysis (EDA) was conducted to assess data quality [3], identify missing or anomalous values, detect trends and seasonal patterns, and better understand the relationships between variables relevant to photovoltaic power generation [3], Figure 1.

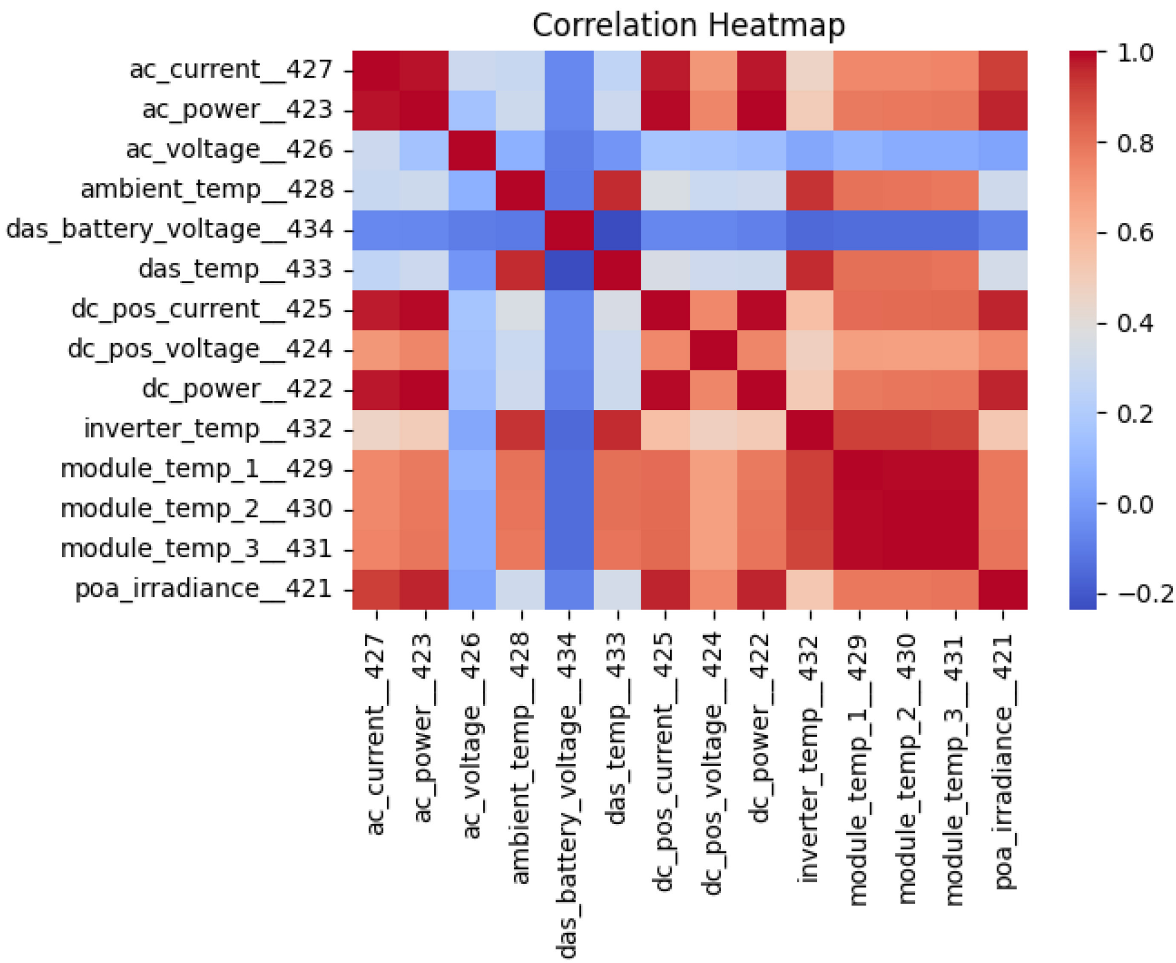

Figure 1. HeatMap

The proposed approach integrates two complementary components for photovoltaic power prediction [12].

The first component is a nonlinear physical model, eq. (1) derived from the fundamental equations governing photovoltaic effects, which provides an initial theoretical estimation of the output power [13].

The second component is a Long Short-Term Memory (LSTM) neural network designed to refine this estimation by learning the residual discrepancies between the measured and physically estimated power values [6].

The physical model is implemented as a function $f(G, V, T)$ encapsulated within a Lambda layer. This layer allows arbitrary computations – here, the physical power estimation – to be seamlessly included in the computational graph of the neural network. This function computes the theoretical photovoltaic power output as a function of irradiance (G), module voltage (V), and cell temperature (T), representing the deterministic part of the system behaviour:

$$P = G \times V \times [1 - \beta \times (T - T_{\mathrm{Ref}})] \tag{1}$$

where are: G - the irradiance (incident solar power), T- the module temperature, V- the electrical voltage, β- the temperature coefficient of the panel efficiency, with this coefficient varying between 0.004 and 0.006 ($\beta = 0.005$), and T_{Ref}- the reference temperature of the panel ($T_{\mathrm{Ref}} = 25$ °C).

Subsequently, the LSTM network models the remaining nonlinearities and temporal dependencies not captured by the physical formulation, thereby adjusting and improving the overall prediction accuracy.

It is important to highlight that LSTM networks are a category of recurrent neural networks specifically designed to learn and retain long-term dependencies in historical data [4]. These models, first introduced by Hochreiter and Schmid Huber, have since been refined and are widely used by many researchers [5]. They are organized into LSTM units, and each unit integrates a memory cell and three gates (input gate, forget gate, and output gate) that regulate the flow of information through the network [6]:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{2}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{3}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{4}$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{5}$$

$$o_i = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \times \tanh(C_t) \tag{7}$$

where are: f_t - the forget gate, i_t - the input gate, $\tilde{C}_t$ - the new cell information, C_t- the memory cell, o_t- the output gate, and h_t - the hidden state.

The output of the physical model and the output of the neural network are added together in the ADD layer to obtain a final prediction [4]. The idea is that the output of the physical model gives an approximation of power based on physical laws, while the LSTM recurrent network refines this prediction by modeling more subtle relationships in the data [7], Figure 2.

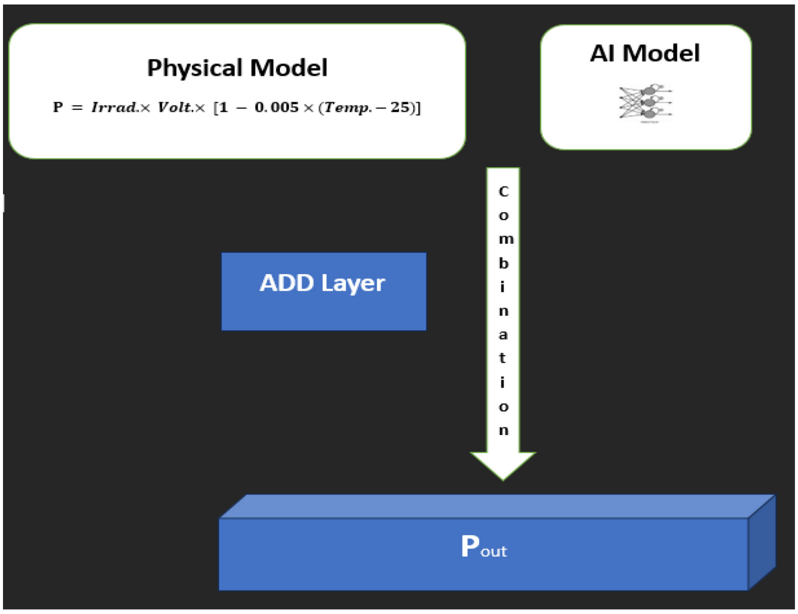

Figure 2. Model architecture

To improve the algorithm's performance, variable selection was performed based on a visual correlation analysis using a heatmap [8]. This graphical representation allowed us to observe the linear relationships between all the variables in the database and the target variable, namely the alternating current power **ac_power__423**.

By identifying the variables with the highest absolute correlation coefficients with the target, nine (9) variables were selected as the most relevant for model training:

- **dc_power__422**: direct current (DC) power, measured at the output of the photovoltaic modules.
- **dc_pos_current__425**: positive DC current from the panels.
- **ac_current__427:** alternating current injected into the grid, directly related to the target variable.
- **poa_irradiance__421**: plane-of-array (POA) irradiance, indicating the amount of solar radiation received.
- **module_temp_3__431**, **module_temp_2__430**, **module_temp_1__429**: temperatures measured at different points on the photovoltaic modules.
- **dc_pos_voltage__424**: positive DC voltage.
- **inverter_temp__432**: internal temperature of the inverter.

The Base 1 dataset was then split, with **80%** allocated for training and **20%** reserved for testing [22].

RESULTS

To evaluate prediction performance, two standard metrics were employed: the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) [9].

Root Mean Squared Error

*RMSE i*s a widely used metric for assessing the performance of regression models [7]. It is the square root of the average of the squared differences between the predicted values $\hat{y}_i$ and the actual values y_i [8]**:**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

where are: y_i- the actual value, $\hat{y}_i$ - the predicted value, and n- the total number of data points.

This metric is sensitive to large errors and retains the same units as the original data, which facilitates interpretation [10].

Mean Absolute Error

The *MAE* measures the average absolute difference between actual values y_i and predicted values $\hat{y}_i$, [11] regardless of the direction of the error [28]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| y_i - \hat{y}_i| \tag{8}$$

where are: y_i- the actual value, $\hat{y}_i$- the predicted value, and n - the total number of data points.

The Table 3 presents the results obtained for four models used to predict AC power output, evaluated using $RMSE$ and MAE.

Table 3. Models comparison

Model	*RMSE*	*MAE*
Model 1: Physical Model	338.55	182.08
Model 2: AI Model (LSTM)	3.29	1.51
Model 3: AI Model (RNN)	2.87	1.33
Model 4: Proposed Hybrid Approach	2.83	1.26

DISCUSSION

The results presented in Table 3 reveal significant differences in performance among the various modeling approaches. Model 1, based on a classical physical modeling technique, shows very high error values ($RMSE = 338.55$ and $MAE = 182.08$), highlighting its inadequacy for accurate predictions in variable environments.

In contrast, Models 2 and 3, built on artificial intelligence architectures (LSTM and RNN), demonstrate significant improvements, with errors reduced by over 99% compared to the physical model. The RNN model ($RMSE = 2.87$; $MAE = 1.33$) slightly outperforms the LSTM model ($RMSE = 3.29$; $MAE = 1.51$), possibly due to a better adaptation to the sequential structures present in time series data.

The proposed Hybrid Approach (Model 4), which integrates a physical model with an LSTM neural network, yields the best performance with an $RMSE$ of 2.83 and an MAE of 1.26. This slight improvement over purely AI-based models highlights the relevance of combining theoretical modeling with neural network learning capabilities [12].

In summary, these results underscore the superiority of artificial intelligence-based methods – particularly the effectiveness of integrating a physical model within a deep learning pipeline.[13] The proposed approach stands out for its accuracy, robustness, and adaptability in photovoltaic power forecasting contexts.

CONCLUSION

This article presents a novel hybrid approach for predicting photovoltaic power, integrating a nonlinear physical model with an LSTM neural network. This multi-resolution strategy effectively combines the theoretical rigor and interpretability of physical models with the adaptability and learning capacity of neural networks, enabling the capture of complex, nonlinear, and temporal dynamics inherent in photovoltaic systems.

Experimental results, assessed using $RMSE$ and MAE metrics, clearly demonstrate that the proposed hybrid model outperforms both conventional physical models and standalone AI models. The substantial reduction in prediction errors highlights the practical effectiveness of this integrative approach, particularly under conditions of high environmental variability and fluctuating solar irradiance.

The study underscores the practical potential of hybrid modelling for smarter and more resilient energy management systems, providing a framework that can enhance decision-making in operational photovoltaic installations. Furthermore, the methodology offers a generalizable approach that could be adapted to other forms of renewable energy generation, broadening its applicability.

For future work, it would be particularly valuable to explore approaches that enable hybrid models to predict photovoltaic power on new installations without relying on historical operational data for training the LSTM component. Developing such a capability would significantly increase the practical utility of hybrid models, allowing rapid deployment and accurate prediction in emerging photovoltaic sites or for systems with limited historical records.

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