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Photovoltaic Power Prediction with Teaching Learning Based Optimization Algorithm

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Abstract

The need for electrical energy has increased considerably due to technological developments. Reducing costs and losses, especially in the supply of electrical energy, is among the goals of energy companies. Photovoltaic energy has been an important alternative in reducing energy costs. However, there are significant power quality problems in transferring the generated photovoltaic energy to the grid. Therefore, the generated photovoltaic energy needs to be accurately estimated to be transferred to the grid smoothly. In the literature, many forecasting models have been used for photovoltaic power forecasting. Each of these forecasting models has estimated photovoltaic power using different input parameters, different estimation intervals, and different estimation algorithms. This paper was conducted using the Teaching-Learning Based Optimization (TLBO) algorithm as an alternative approach to photovoltaic power forecasting models. According to the forecasting results, the root mean square error (RMSE) for the test subset was obtained as 270.32 kW, and the mean absolute percentage error (MAPE) was found to be 3.87%. These results indicate that the TLBO algorithm demonstrates high accuracy for photovoltaic power forecasting and provides an effective alternative model in this field.

Cite

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1. INTRODUCTION

With the escalation of the energy crisis, renewable energy sources like photovoltaic (PV) power, wind energy, and hydropower have garnered significant interest from numerous nations globally. Photovoltaic (PV) electricity is a significant contributor to the continuous, steady, and cost-effective functioning of power networks among the most prevalent renewable energy sources (Lin et al., 2022). In reaction to the growing need for renewable energy, photovoltaic power generation is consistently rising. The International Renewable Energy Agency (IRENA, 2024) projects that global renewable energy capacity will attain 3870 GW by the conclusion of 2023. Solar energy has the largest share in the global total with 1419 GW of capacity. Hydropower and wind power accounted for most of the rest, with total capacities of 1268 GW and 1017 GW, respectively (IRENA, 2024). Renewable energy capacity by source is shown in Figure 1.

Renewable energy capacity increased by 473 GW in 2023. Solar power continued to lead capacity growth with a large increase of 346 GW, followed by wind power with 116 GW. Solar and wind continued to dominate renewable capacity growth, together accounting for 97.6% of all net renewable capacity additions in 2023. The expansion of wind and solar energy has resulted in the highest annual increase in renewable generation capacity, as well as the highest percentage growth on record (IRENA, 2024). However, due to the randomness, uncertainty, and variability in photovoltaic power generation, there are significant challenges in connecting large-scale photovoltaic systems to the grid (Maghami et al., 2016). The fluctuation and intermittency of

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photovoltaic power can cause unexpected losses in existing electricity systems (Liu et al., 2018). In addition, the unstable nature of photovoltaic power systems can lead to power outages, voltage fluctuations, and grid inefficiency. It is therefore evident that research into accurate prediction of photovoltaic power output and the facilitation of integration of photovoltaic power into the grid represents a significant and growing area of interest within the field of photovoltaic power generation (Saber et al., 2014). This is because the impact of power quality problems caused by photovoltaic systems can be reduced or completely eliminated by predicting the photovoltaic power to be generated. Figure 2 shows the increase in renewable energy capacity.

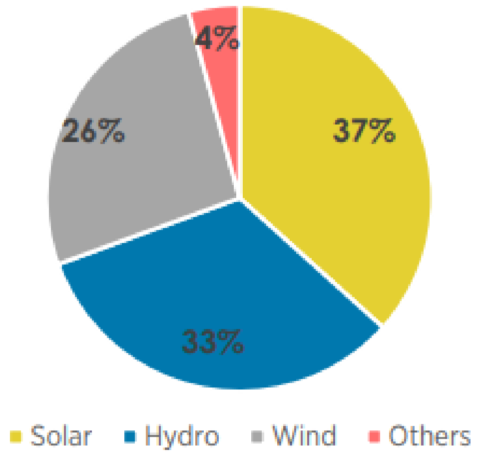


Figure 1. *Renewable energy capacity by energy source (IRENA, 2024)*

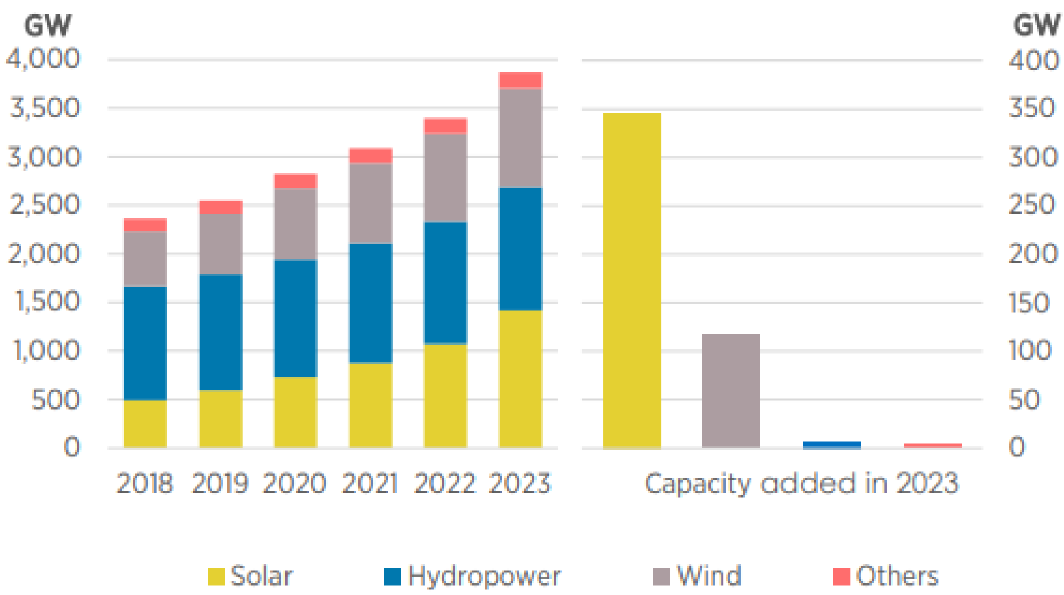


Figure 2. *Renewable energy capacity growth (IRENA, 2024)*

As a result of advances in artificial intelligence technology, photovoltaic power forecasting is performed in very short-term, short-term, medium-term, and long-term periods (Li et al., 2020). The four different time horizons used for photovoltaic power forecasting and their purposes can be explained as follows (Kleissl, 2013; Elsinga & Van Sark, 2017): The very short-term period covers forecasts of up to 15 minutes for load following, reserve capacity planning, and power quality. The short-term period includes forecasts between 15 minutes and 1 hour for market bidding, load following, and reserve capacity planning. The medium-term period covers forecasts from 1 hour to 1 day for baseload planning and market bidding. The long-term period includes forecasts beyond 1 day for energy management, power capacity dispatch, and market bidding. The different time horizons and purposes used in photovoltaic power forecasting are shown in Table 1.

Table 1. *Applicability of photovoltaic power estimation at different times*

Horizons	Period	Purposes
Ultra-short-term	One second to 15 minutes	Load following, reserve capacity planning, power quality
Short-term	15 minutes to one hour	Market bidding, load following, reserve capacity planning
Medium-term	One hour to one day	Base-load planning, market bidding
Long-term	Prediction after one day	Energy management, distribution of power capacity, market bidding

Photovoltaic power estimation can be categorized under three main headings: physical models, statistical methods, and machine learning models (Das et al., 2018). Physical models use the mathematical relationship between solar radiation and photovoltaic power output. These models are calculated based on numerical weather forecasts or satellite data. Statistical methods allow us to infer correlation and variation patterns based on statistical principles by analyzing historical data. However, since they focus on historical data, they usually neglect weather conditions (Tang et al., 2022). Machine learning methods, on the other hand, can learn the relationships between data by training large data sets. Therefore, they require less input than physical models (Dosdoğru & İpek, 2022). It is therefore possible to make direct predictions about future PV power by utilising historical data on PV power and meteorological variables.

The development of effective solar energy forecasting methods is of great significance in ensuring the optimal utilisation of renewable energy sources. In this context, the primary objective of the present study is to devise an alternative and efficacious model for solar energy forecasting. In this forecasting study, conducted using current data, particulate matter (PM10), one of the air pollution parameters, was included as an input variable alongside commonly used input data. This approach represents a pivotal contribution of the study.

2. PHOTOVOLTAIC POWER PREDICTION

A review of similar studies in the literature reveals the diversity of research on photovoltaic power forecasting and the difference in the methods used. Comparisons on the input data used for each forecasting model, forecasting models, forecasting period, forecasting accuracy, and the results obtained form the basis of the research in the literature. The studies in the literature generally cover very short, short, medium, and long-term periods. The literature review based on these periods is presented in detail in Table 2 to Table 5. While there is a range of estimates for photovoltaic power in the literature, the estimates in Table 1 are used as a reference for Table 2 through Table 5.

Table 2. *Photovoltaic power predicted methods based on a very short-term period*

Ref.	Input data	Prediction models	Prediction periods	Prediction accuracies	Prediction results
(Amarasinghe & Abeygunawardane, 2018)	Air temperature, global horizontal radiation, solar radiation, wind speed, global diffuse radiation	Artificial neural network (ANN)	1-min	RMSE=0,035 MAE=0,0117	ANN>SP
		Smart persistence (SP)		RMSE=0,1015 MAE=0,048	
(Han et al., 2019)	Wind speed, solar radiation, humidity, temperature	Kernel density estimation (KDE)	15-min	MAE(W)=1,88 RMSE(W)=4,19	KDE
(VanDeventer et al., 2019)	Photovoltaic power, ambient temperature, solar radiation	Genetic-algorithm-based support vector macihine (GASVM)	15-min	RMSE(W)=100,47 MAPE(%)=1,7	GASVM>SVM
		Suport vector machine (SVM)		RMSE(W)=680,85 MAPE(%)=11,22	

Table 3. *Photovoltaic power predicted methods based on short-term periods*

Ref.	Input data	Prediction models	Prediction periods	Prediction accuracies	Prediction results
(Das, 2021)	Photovoltaic power	Auto-regressive integrated moving average (ARIMA)	30-min	MAE=699,9 RMSE(W)=821,6	ARIMA>AM
		Analytical method (AM)		MAE=39117,2 RMSE(W)=39300,7	
(Korkmaz, 2021)	Solar radiation, temperature, photovoltaic power	Convolutional neural network (CNN)	1-h	R^2=0,9871 RMSE(kW)=0,309 MAE(kW)=0,175	CNN
(Cheng et al., 2019)	Surface solar radiation, solar radiation, relative humidity, surface temperature, average temperature, wind speed at 10m	Improved grey wolf optimizer algorithm (IMGWO)	1-h	RMSE=0,065	IMGWO>SPGP
		Sparse Gaussian process (SPGP)		RMSE=0,069	
(Theocharides et al., 2020)	Photovoltaic power, meteorological data, numerical weather forecast data	Artificial neural network (ANN)	1-h	nRMSE(%)=6,11 MAPE(%)=4,7	ANN

Table 4. *Photovoltaic power predicted methods based on medium-term period*

Ref.	Input data	Prediction models	Prediction periods	Prediction accuracies	Prediction results
(Ma & Zhang, 2022)	Solar radiation, temperature, relative humidity	Modified Firefly Algorithm (MFA) Elman artificial neural network (Elman)	1-day	MAE(kW)=1,12 MSE(kW)=1,69 RMSE(kW)=1,30	MFA-Elman> FA-Elman> Elman
		Firefly-based Elman neuronal network (FA-Elman)		MAE(kW)=1,56 MSE(kW)=2,98 RMSE(kW)=1,73	
		Elman neural network (Elman)		MAE(kW)=2,36 MSE(kW)=7,84 RMSE(kW)=2,80	
(Irmak et al., 2023)	Solar radiation, power output, temperature, relative humidity	Artificial neural network (ANN)	1-day	RMSE(kW)=2178,1 MAPE(%)=3,83	ANN
	Solar radiation, power output, PM10, temperature			RMSE(kW)=984,7 MAPE(%)=1,86	
(Irmak et al., 2024)	Temperature, power output, PM10, solar radiation	Artificial neural network based on the JAYA algorithm (JAYA-ANN)	1-day	RMSE(kW)=650,44 MAPE(%)=2,72	JAYA-ANN> ANN
		Artificial neural network (ANN)		RMSE(kW)=841,90 MAPE(%)=3,93	
(Qu et al., 2021)	Photovoltaic power	Single gated recurrent unit (SGRU)	1-day	NRMSE(%)=18,31 NMAE(%)=13,67	GRUP>MGRU> SGRU
		Gated recurrent unit pool (GRUP)		NRMSE(%)=6,83 NMAE(%)=4,12	
		Multiple gated recurrent unit (MGRU)		NRMSE(%)=14,5 NMAE(%)=11,18	

Table 5. *Photovoltaic power predicted methods based on long-term period*

Ref.	Input data	Prediction models	Prediction periods	Prediction accuracies	Prediction results
(Moreira et al., 2021)	Relative humidity, rainfall, ambient temperature, sunshine duration, cloudiness	Artificial neural network (ANN)	1-week	MAPE(%)=4,70	ANN
(Dandıl & Gürgen, 2019)	Current, voltage	Clonal selection algorithm (CSA)	1-month	MAPE(%)=1,629 RMSE=1,96	PSO>BP>CSA
		Back-propagation neural network (BP)		MAPE(%)=0,398 RMSE=0,520	
		Particle swarm optimization (PSO)		MAPE(%)=0,206 RMSE=0,270	
(Liang et al., 2023)	Air pressure, humidity, temperature, solar radiation, wind speed and direction	Fast outlier culling algorithm based decision trees-Improved whale bat optimisation algorithm-Least squares support vector regression (FCDT-IWBOA-LSSVR)	1-month	R2=0,983 MSE(kW)=1,913 RMSE(kW)=1,383 MAE(kW)=0,625	FCDT-IWBOA-LSSVR

As a result of the review of studies on photovoltaic power forecasting, the following useful conclusions can be drawn:

- Air temperature, solar radiation, and photovoltaic power parameters are the main parameters used for forecasting. Besides these primary parameters, secondary parameters such as relative humidity and wind speed are also important. However, some input parameters are less commonly used. For example, variables such as air pressure, rainfall, cloud cover, sunshine duration, and sky index are among these parameters.
- Artificial neural networks are one of the most widely used methods for the prediction of the power output of photovoltaic systems. After neural networks, other methods such as support vector machines, support vector regression, and autoregressive integrated moving averages come next and offer alternative approaches for photovoltaic power forecasting. However, collective learning aims to achieve more accurate results by combining different forecasting models. Exogenous variable-driven autoregressive modeling forecasts by taking into account the effects of exogenous variables (e.g. cloudiness, wind speed, etc.) on solar power generation. Radial basis functions allow the modeling of complex relationships by transforming input data. Recurrent neural networks and multilayer perceptrons are used to analyze time series data.
- Time intervals have an important role in the photovoltaic power forecasting process and are usually categorized according to specific periods. These time intervals affect the accuracy and precision of the forecasting methods. Studies generally cover very short-term, short-term, and mid-term forecasting periods. In particular, 15 minutes (very short term), 1 hour (short term), and 1 day (medium term) are the time intervals used for forecasting.
- Error measures are an essential component in the evaluation of photovoltaic power forecasts, as they provide insight into the discrepancies between predicted power values and actual observations. Commonly employed metrics for assessing the accuracy, precision, and reliability of prediction models include the mean absolute error, normalised root mean square error, mean absolute percentage error, and root mean square error.
- The breadth of the data input area in photovoltaic power forecasting can substantially influence the accuracy of the predictions. This indicates that an extensive data input area enables the forecasting model to utilize a broader array of information, hence enhancing prediction accuracy. Moreover, an extensive input data space enables the model to learn from a greater volume of data and to evaluate

the interrelationships among this data with enhanced precision. This enables the forecasting algorithm to generate more consistent and dependable forecasts.

- During seasons when weather variables change less, solar power systems exhibit a more constant performance. This makes it easier for forecasting models to more accurately predict future power generation based on historical data. Especially in summer, solar radiation and air temperature are generally more stable, which can contribute to more consistent results from forecasting models.
- In photovoltaic power forecasts, it is observed that forecast accuracy increases with decreasing forecast time. This suggests that forecasts with shorter time intervals may provide more reliable results. However, each forecast interval and method should be evaluated depending on specific conditions and requirements. For example, while short-term forecasts may be appropriate for maintaining the supply-demand balance on the power side, long-term forecasting is required to assess the economic situation. Therefore, a delicate balance must be maintained when determining the right forecasting strategies.
- In photovoltaic power forecasting, it was observed that the success rate of the forecasting model increased when the sampling time was reduced, i.e. in scenarios where data was collected more frequently and forecasts were updated more frequently. This suggests that more frequent data collection can improve forecast accuracy by enabling faster adaptation to current conditions. However, more frequent sampling and updating can increase data collection and processing costs. Furthermore, forecasts that are updated too frequently indicate that systems need to be constantly monitored and managed, which can increase operational burdens.
- The types of panels used in photovoltaic power estimation are an important factor that can affect the accuracy of the estimation. The different characteristics of these panels can cause differences in the perception and estimation of the factors affecting solar power generation.
- Hybrid models used in photovoltaic power forecasting, i.e. models that combine more than one forecasting method or model, have generally shown better performance. This success of hybrid models can be attributed to the fact that they combine the strengths of different forecasting methods to compensate for weaknesses and improve forecasting accuracy. However, building and optimizing hybrid models is often complex and requires a precise modeling and evaluation process.
- An important aspect is often overlooked in the literature, especially about the reliability and accuracy of forecasts: forecast intervals and forecast errors. In many studies, forecast intervals and forecast errors are not specified. This makes it difficult for researchers to assess the reliability of estimates and prevents monitoring changes over time. To increase the quality of studies and the credibility and transparency of the scientific knowledge production process, estimation intervals and errors should be specified.
- Photovoltaic power forecasts are critical to improve the efficiency of solar systems and optimize energy management. However, it would be useful to present commonly used error scales to assess the accuracy of these forecasts, as well as improvement percentages concerning the continuity reference model to enable appropriate benchmarking tests.

3. TEACHING LEARNING BASED OPTIMIZATION ALGORITHM

TLBO is a meta-heuristic algorithm that simulates the educational impact of an instructor on students in a classroom environment. This algorithm operates in two main stages: the teacher phase and the student phase. During the teacher phase, the instructor conveys knowledge to students, facilitating their progress. Conversely, the student phase models peer-to-peer learning, where students interact to share knowledge among themselves. Within the algorithm, the population represents the students and teacher, with the individual yielding the best solution taking the role of the class teacher. Initially, a random population is generated, and the individual with the highest objective function value is assigned as the teacher. In the teacher phase, this teacher attempts to raise the knowledge level of other individuals to match their own. In the student phase, the algorithm models student interactions, enabling mutual learning and improvement. This iterative process aims to enhance the solution quality generated by the algorithm (Rao et al., 2012; Rao & Patel, 2013).

• Teacher phase: In this phase, the teacher instructs the students and improves the current average result in the nth iteration. The difference in average results is calculated as shown in Equation 1.

$$\Delta MR_n = rand[(NM_n) - (TF_n \times MR_n)] \; where \;\; TF_n = \left(\frac{MR_n}{NM_n}\right) \tag{1}$$

Here, NM_n represents the new mean, MR_n denotes the mean results, and TF_n stands for the teaching factor. Based on the obtained difference in mean results, the current solution is updated according to Equation 2.

$$Xnew_n = Xold_n + \Delta MR_n \tag{2}$$

$Xnew_n$, given in Equation 2, is the updated value of $Xold_n$, and all $Xnew_n$ values are stored and passed as input to the student phase.

• Student phase: The knowledge of any student increases through interaction with other students, and the students' knowledge is updated according to Equations 3 and 4.

$$Xnew_n = Xold_n + rand(X_k - X_m), \;\; if \; f(X_k) < f(X_m) \tag{3}$$

$$Xnew_n = Xold_n + rand(X_m - X_k), \;\; if \; f(X_m) < f(X_k) \tag{4}$$

Here, X_k and X_m are randomly selected students, and the updated student value with the better fitness value is retained. The flow diagram of the TLBO method is given in Figure 3.

4. RESULTS OF THE PREDICTION OF THE PHOTOVOLTAIC POWER WITH THE TLBO ALGORITHM

In this study, solar radiation, particulate matter (PM10), ambient temperature, and historical power data were used for daily photovoltaic power forecasting. The dataset used in the study consists of daily recorded data over a three-month period. The TLBO algorithm was applied in the forecasting process, and the forecast results were analyzed separately for the training and test subsets. To evaluate the accuracy of the forecasting model, mean absolute percentage error (MAPE) and root mean square error (RMSE) metrics were employed. The MAPE value was calculated using Equation 5, while the RMSE value was calculated using Equation 6.

$$\text{MAPE} = \frac{1}{n}\sum_{\text{i}=1}^{n}\left(\frac{t_\text{i} - p_\text{i}}{t_\text{i}}\right) \times 100 \tag{5}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{\text{i}=1}^{n}(t_\text{i} - p_\text{i})^2} \tag{6}$$

In the aforementioned equations, t_i signifies the actual measured value, p_i symbolizes the anticipated value, and n represents the total number of data points. The forecasting model was trained on a dataset consisting of 70% of the total data and evaluated on a test dataset comprising the remaining 30%.

Using the dataset, the MAPE values for the TLBO-based forecasting study were found to be 7.20% and 3.87% for the training and test subsets, respectively, while the RMSE values were 325.64 kW and 270.32 kW. The TLBO predictions and actual power production for the training and test subsets are shown in Figure 4.

For the forecast made using the entire dataset with the TLBO model, the MAPE value was found to be 6.18%, and the RMSE value was 241.02 kW. Figure 5 presents the actual power production and the TLBO model's forecast results for the complete dataset.

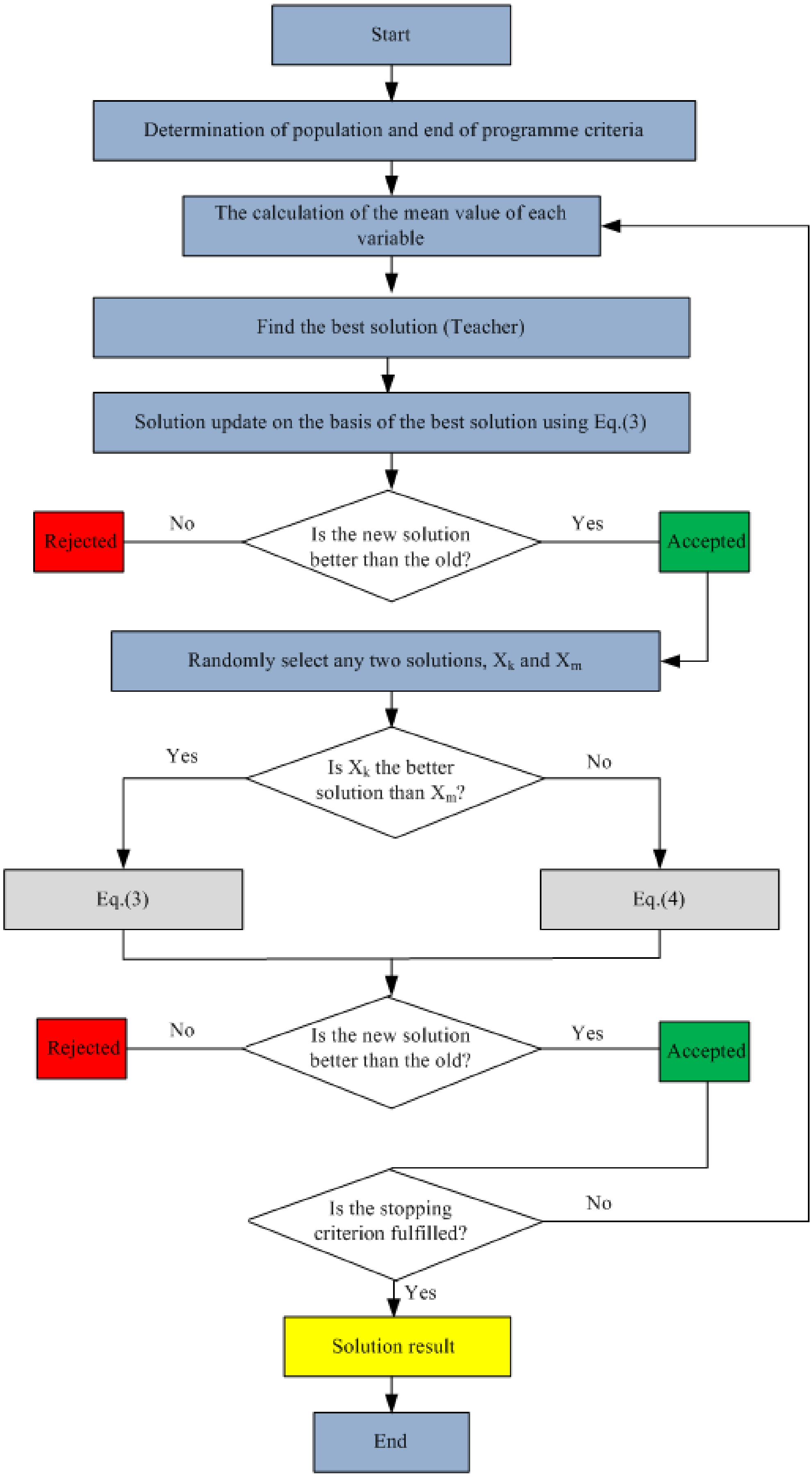
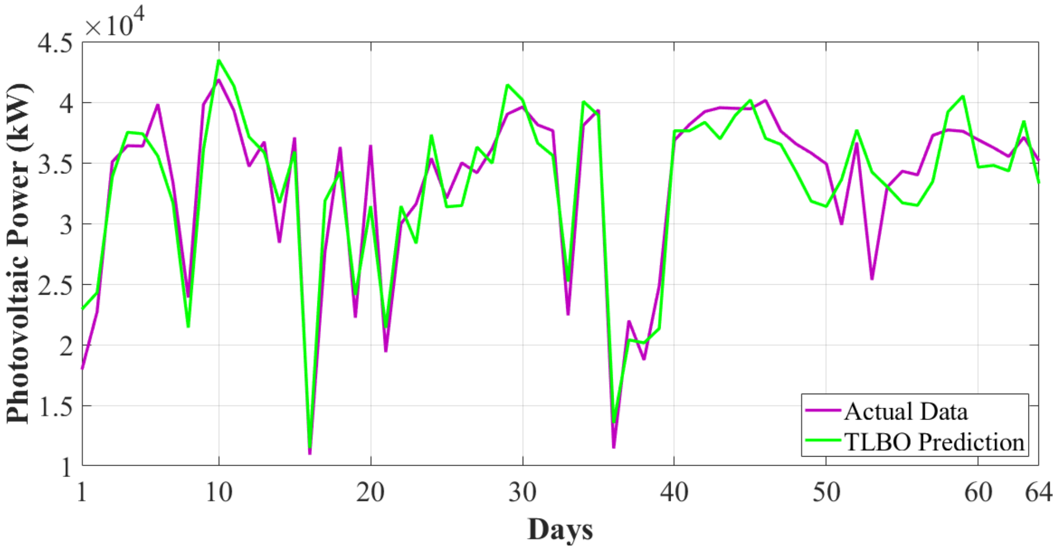
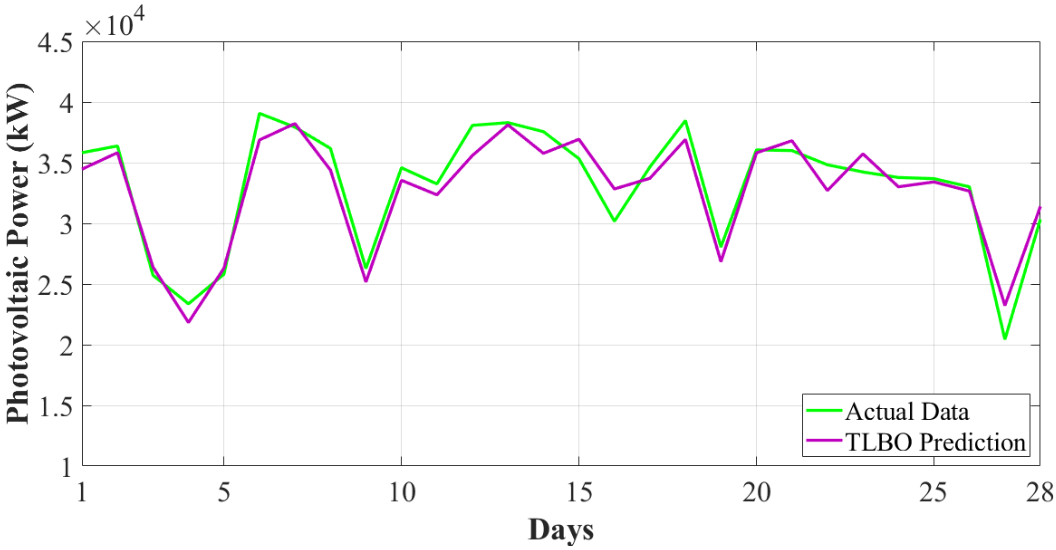


Figure 3. *TLBO flow diagram*



(a)



(b)

Figure 4. a) *Training subset,* ***b)*** *Test subset*

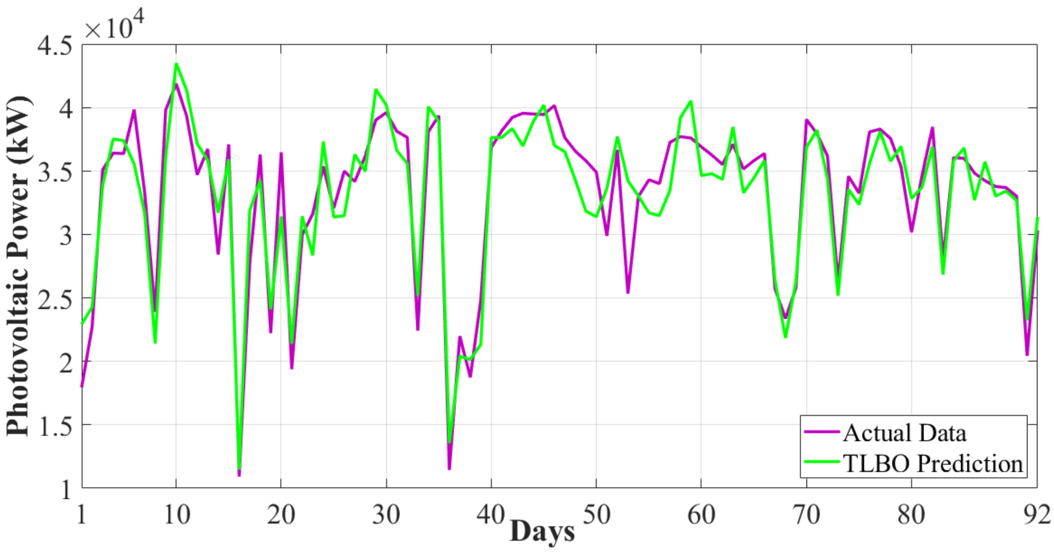


Figure 5. *TLBO prediction and actual power generation*

The proposed TLBO forecasting model has yielded highly successful results in photovoltaic power forecasting. The MAPE and RMSE values obtained from the forecast are presented in Table 6.

Table 6. *MAPE and RMSE values*

	MAPE (%)	**RMSE (kW)**
Data Set (training)	7.20	325.64
Data Set (test)	3.87	270.32
Data Set (all)	6.18	241.02

5. CONCLUSION

The objective of this study is to develop a TLBO model for the purpose of forecasting photovoltaic power generation. The developed TLBO model demonstrated highly successful performance in photovoltaic power forecasting, as evidenced by a MAPE of 3.87% and a RMSE of 270.32 kW obtained for the test subset. These performance results indicate that the TLBO algorithm makes a significant contribution, particularly in supporting day-ahead planning and ensuring the stability of power systems. By enabling the prediction of fluctuations in solar energy-based power generation, the model contributes to maintaining grid balance more effectively. In addition, the proposed TLBO model has enabled more accurate and stable results in photovoltaic power forecasting, establishing itself as an alternative method to other forecasting models in the literature. Future studies are encouraged to examine the performance of the TLBO model in more detail by considering different forecasting horizons, seasonal variations, and diverse input data. In this context, comparing the model under various climate conditions and with different data sources is deemed essential to assess its generalizability and potential for broader application.

CONFLICT OF INTEREST

The author declares no conflict of interest.

REFERENCES

Amarasinghe, G., & Abeygunawardane, S. (2018). An artificial neural network for solar power generation forecasting using weather parameters. In: Proceedings of the 112th Annual Sessions, Institution of Engineers Sri Lanka, (pp. 431-438), Colombo, Sri Lanka.

Cheng, Z., Liu, Q., & Xing, Y. (2019). A hybrid probabilistic estimation method for photovoltaic power generation forecasting. *Energy Procedia*, *158*, 173-178. http://www.doi.org/10.1016/j.egypro.2019.01.066

Dandıl, E., & Gürgen, E. (2019). Yapay Sinir Ağları Kullanılarak Fotovoltaik Panel Güç Çıkışlarının Tahmini ve Sezgisel Algoritmalar ile Karşılaştırılması. *Avrupa Bilim ve Teknoloji Dergisi*, *16*, 146-158. http://www.doi.org/10.31590/ejosat.540262

Das, S. (2021). Short term forecasting of solar radiation and power output of 89.6 kWp solar PV power plant. *Materials Today: Proceedings*, *39*, 1959-1969. http://www.doi.org/10.1016/j.matpr.2020.08.449

Das, U. K., Tey, K. S., Seyedmahmoudian, M., Mekhilef, S., Idris, M. Y. I., Deventer, W. V., Horan, B. & Stojcevski, A. (2018). Forecasting of photovoltaic power generation and model optimization: A review. *Renewable and Sustainable Energy Reviews*, *81*, 912-928. http://www.doi.org/10.1016/j.rser.2017.08.017

Dosdoğru, A. T., & İpek, A. B. (2022). Hybrid boosting algorithms and artificial neural network for wind speed prediction. *International Journal of Hydrogen Energy*, *47*(3), 1449-1460. http://www.doi.org/10.1016/j.ijhydene.2021.10.154

Elsinga, B., & Van Sark, W. G. J. H. M. (2017). Short-term peer-to-peer solar forecasting in a network of photovoltaic systems. *Applied Energy*, *206*, 1464-1483. http://www.doi.org/10.1016/j.apenergy.2017.09.115

Han, Y., Wang, N., Ma, M., Zhou, H., Dai, S., & Zhu, H. (2019). A PV power interval forecasting based on seasonal model and nonparametric estimation algorithm. *Solar Energy*, *184*, 515-526. http://www.doi.org/10.1016/j.solener.2019.04.025

IRENA, International Renewable Energy Agency. (2024). Renewable capacity highlights. (Accessed:04/09/2024) https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Mar/IRENA_RE_Capacity_Highlights_2024.pdf?rev=7692ae29458142dd8563618f496e0abb

Irmak, E., Yesilbudak, M., & Tasdemir, O. (2023, June 4-7). *Daily prediction of PV power output using particulate matter parameter with artificial neural networks*. In: Proceedings of the 11th International Conference on Smart Grid (icSmartGrid), (pp. 499-502). Paris, France. https://doi.org/10.1109/icSmartGrid58556.2023.10171103

Irmak, E., Yeşilbudak, M., & Taşdemir, O. (2024). Enhanced PV Power Prediction Considering PM10 Parameter by Hybrid JAYA-ANN Model. *Electric Power Components and Systems*, *52*(11), 1998-2007. http://www.doi.org/10.1080/15325008.2024.2322668

Korkmaz, D. (2021). SolarNet: A hybrid reliable model based on convolutional neural network and variational mode decomposition for hourly photovoltaic power forecasting. *Applied Energy*, *300*, 117410. http://www.doi.org/10.1016/j.apenergy.2021.117410

Kleissl, J. (2013). *Solar energy forecasting and resource assessment*. Academic Press.

Li, P., Zhou, K., Lu, X., & Yang, S. (2020). A hybrid deep learning model for short-term PV power forecasting. *Applied Energy*, *259*, 114216. http://www.doi.org/10.1016/j.apenergy.2019.114216

Liang, L., Su, T., Gao, Y., Qin, F., & Pan, M. (2023). FCDT-IWBOA-LSSVR: An innovative hybrid machine learning approach for efficient prediction of short-to-mid-term photovoltaic generation. *Journal of Cleaner Production*, *385*, 135716. http://www.doi.org/10.1016/j.jclepro.2022.135716

Lin, W., Zhang, B., Li, H., & Lu, R. (2022). Multi-step prediction of photovoltaic power based on two-stage decomposition and BILSTM. *Neurocomputing*, *504*, 56-67. http://www.doi.org/10.1016/j.neucom.2022.06.117

Liu, L., Zhao, Y., Chang, D., Xie, J., Ma, Z., Sun, Q., Yin, H., & Wennersten, R. (2018). Prediction of short-term PV power output and uncertainty analysis. *Applied Energy*, *228*, 700-711. http://www.doi.org/10.1016/j.apenergy.2018.06.112

Ma, X., & Zhang, X. (2022). A short-term prediction model to forecast power of photovoltaic based on MFA-Elman. *Energy Reports*, *8*, 495-507. http://www.doi.org/10.1016/j.egyr.2022.01.213

Maghami, M. R., Hizam, H., Gomes, C., Radzi, M. A., Rezadad, M. I., & Hajighorbani, S. (2016). Power loss due to soiling on solar panel: A review. *Renewable and Sustainable Energy Reviews*, *59*, 1307-1316. http://www.doi.org/10.1016/j.rser.2016.01.044

Moreira, M. O., Balestrassi, P. P., Paiva, A. P., Ribeiro, P. F., & Bonatto, B. D. (2021). Design of experiments using artificial neural network ensemble for photovoltaic generation forecasting. *Renewable and Sustainable Energy Reviews*, *135*, 110450. http://www.doi.org/10.1016/j.rser.2020.110450

Rao, R. V., & Patel, V. (2013). An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems. *Scientia Iranica*, *20*(3), 710-720. http://www.doi.org/10.1016/j.scient.2012.12.005

Rao, R. V., Savsani, V. J., & Balic, J. (2012). Teaching-learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems. *Engineering Optimization*, *44*(12), 1447-1462. http://www.doi.org/10.1080/0305215X.2011.652103

Qu, Y., Xu, J., Sun, Y., & Liu, D. (2021). A temporal distributed hybrid deep learning model for day-ahead distributed PV power forecasting. *Applied Energy*, *304*, 117704. http://www.doi.org/10.1016/j.apenergy.2021.117704

Saber, E. M., Lee, S. E., Manthapuri, S., Yi, W., & Deb, C. (2014). PV (photovoltaics) performance evaluation and simulation-based energy yield prediction for tropical buildings. *Energy*, *71*, 588-595. http://www.doi.org/10.1016/j.energy.2014.04.115

Tang, Y., Yang, K., Zhang, S., & Zhang, Z. (2022). Photovoltaic power forecasting: A hybrid deep learning model incorporating transfer learning strategy. *Renewable and Sustainable Energy Reviews*, *162*, 112473. http://www.doi.org/10.1016/j.rser.2022.112473

Theocharides, S., Makrides, G., Livera, A., Theristis, M., Kaimakis, P., & Georghiou, G. E. (2020). Day-ahead photovoltaic power production forecasting methodology based on machine learning and statistical post-processing. *Applied Energy*, *268*, 115023. http://www.doi.org/10.1016/j.apenergy.2020.115023

VanDeventer, W., Jamei, E., Thirunavukkarasu, G. S., Seyedmahmoudian, M., Soon, T. K., Horan, B., Mekhilef. S., & Stojcevski, A. (2019). Short-term PV power forecasting using hybrid GASVM technique. *Renewable Energy*, *140*, 367-379. http://www.doi.org/10.1016/j.renene.2019.02.087