SVU-International Journal of Engineering Sciences and Applications (2022) 3(2): 123-130
Print ISSN 2785-9967 | Online ISSN 2735-4571
DOI 10.21608/svusrc.2022.157039.1066

# Machine Learning Method for Solar PV Output Power Prediction

**Abdel-Nasser Sharkawy[1]□, Mustafa M. Ali[1], Hossam H. H. Mousa[2], Ahmed S. Ali[4], G. T. Abdel-Jaber[3]**
(Abdel-Nasser Sharkawy, https://orcid.org/0000-0001-9733-221X)

**Abstract** To deal with the challenges of the solar photovoltaic (PV) energy source due to the continuous variations of the climatic conditions such as temperature and solar radiation, output power prediction is one of the most important research trends nowadays. In this paper, a multilayer feedforward neural network (MLFFNN) is executed to foresee the power for a solar PV power station. The MLFFNN employs the temperature and radiation as the inputs and the power as the output. For training and testing the MLFFNN, data of 6 days are acquired from a real PV power station in Egypt. The first five days are employed to train the MLFFNN using Levenberg-Marquardt (LM) algorithm. While the data of the sixth day, are used to check the effectiveness and the generalization ability of the trained MLFFNN. The results prove that the trained MLFFNN is working very well and efficient to predict the PV output power correctly.

**Keywords:** Power Prediction; Multilayer Feedforward NN; Solar PV; Levenberg-Marquardt Algorithm; MLFFNN Effectiveness.

## 1 Introduction

Energy crisis, environmental change, and rising pollution levels are critical issues that continue to drive the shift away from fossil fuels and toward renewable sources of energy. The Paris Agreement, which was ratified by 196 countries in 2015 and came into force in November 2016, lays out a strategy for limiting global warming by driving countries to eradicate traditional energy sources (TESs) and depend on a circle economy [1], [2]. Energy planners and academics are working hard to connect different renewable energy sources (RESs) to the utility grid to reduce the TESs hazards.

Different types of RESs depend on climatic conditions to produce electrical power [3], [4]. The energy generated by these RESs constantly changes according to the change in climatic conditions. The efficiency of wind turbines is based on the direction and the speed of the wind. For thermal solar and PV systems, solar irradiation, air temperature, and humidity are the most important factors that control the power generation and the PV system's performance. The stability of the system's performance and electrical power is the major challenge for modern power grids. Forecasting the output power from various RESs is the main reason for the stability of the system, by helping to develop a control system that allows maintaining the energy produced at its specified value.

Solar photovoltaic (PV) cells are one of the basic technologies for transforming solar radiation into electricity [5]. The intermittent and stochastic nature of solar energy has posed significant hurdles to power networks in terms of operation and control due to potentially unforeseen solar

Received: 18 August 2022/ Accepted: 28 August 2022
□Corresponding Author: Abdel-Nasser Sharkawy, E-mail: abdelnassersharkawy@eng.svu.edu.eg, eng.abdelnassersharkawy@gmail.com
1 Mechatronics Engineering, Department of Mechanical Engineering, South Valley University, Qena 83523, Egypt.
2 Department of Electrical Engineering, South Valley University, Qena 83523, Egypt.
3 Department of Mechanical Engineering, South Valley University, Qena 83523, Egypt.
4 Mechatronics Engineering, Department of Mechanical Engineering, Assiut University, Assiut, Egypt.

grid fluctuations. The growth in the solar PV output power in the world from 2009 until 2019 increased from 23 GW to 127 GW respectively, as presented in Fig. 1, [6].

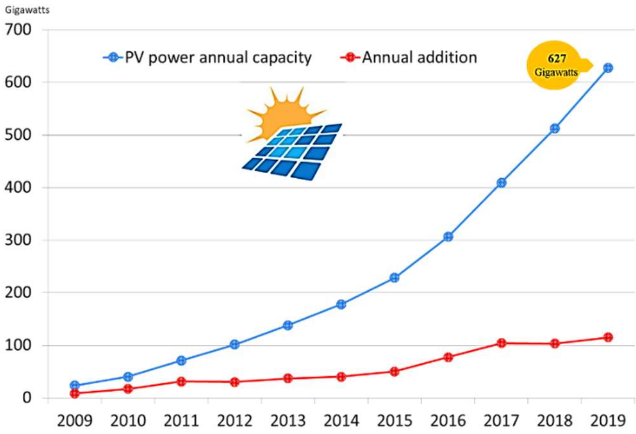



**Fig. 1** Solar PV annual capacity, [6].

For controlling the utility grid indices during the integration of the solar PV output power, it is essential to develop accurate models for energy production forecasting based on the climate conditions. The prediction horizon can be defined as short-term, medium-term, or long-term which is considered the most important factor in deciding the suitable strategy for the prediction of solar PV power. These methods were executed based on mathematical analysis, one diode model using four parameters, a partial functional linear regression model, and finally machine learning such as support vector machine (SVM) and neural network (NN) algorithms.

Hence, mathematical prediction methods [7]–[10] such as the persistence model and statistical approaches were used. However, these methods provided poor forecasting precision with high sensitivity to weather variations. On the other hand, methods established on machine learning such as SVM and NNs were proposed for predicting the PV power. In [11], the proposed method predicted one-hour ahead of PV output power based on SVM and random forest using various weather data such as temperature, humidity, rainfall, and wind speed. The NN has the properties that it can approximate any function and its ability of generalization under different conditions [12], [13]. In [14], three NN systems (Elman NN, feed-forward (FF)NN, and Generalized regression (GR)NN) were employed to forecast the solar PV system with several inputs like solar cell location, and solar radiation, the wind velocity, and the ambient temperature. Their acquired results confirmed that the NN systems produced accurate predictions with a root mean squared error (RMSE) of 0.25 in ELMAN NN and 0.30 in FFNN and 0.426 in GRNN. The effectiveness and the generalization ability of these NNs were not considered and appraised under altered circumstances. Several NN systems also were proposed for power prediction in the following references [15]–[17]. The main gap in these references was that the effectiveness of the NN under different conditions and data was not examined. In addition, the accuracy of the PV power prediction method needs further investigations and to be improved/increased.

The main contribution and novelty of this paper is discussed as follows.

According to the increased penetration of the solar PV substations into the utility grid, the necessity to integrate new advanced control methods to avoid the disturbances and operation interruptions of the electrical power or blackout under continuous variations of weather data. So, the machine learning algorithm is applied to forecast the upcoming output power with very limited error in the various real applications to ensure the well continuous operation. The precise solar PV power prediction is employed using a simple MLFFNN which is proposed and designed to predict the power using only two main inputs (the module temperature and the solar radiation). The training of this designed NN is performed using real data from a PV plant in Egypt and using Levenberg-Marquardt (LM) algorithm. To evaluate the prediction accuracy, the mean squared error (MSE) and the training error (TE) are used. Moreover, the generalization ability and the effectiveness of the trained MLFFNN are then checked and investigated using different data than the ones used for the training process. The results show that the MLFFNN is trained very well, and the MSE and the training error are very low and close to zero. Therefore, the trained MLFFNN can foresee the solar PV output power with high accuracy in any weather condition.

The rest of the paper is divided as follows: section 2 provides mathematical analysis for calculating the output power of the PV plant. In section 3, the design, the training, and the testing of the MLFFNN for predicting the power are presented in detail. The training process is carried out using data from five days obtained from the real PV power station in Egypt. Section 4 illustrates the effectiveness of the trained MLFFNN using data from the six day which is not used for the training. Section 5 summarizes the main points presented in this paper and gives some future work.

## 2. Solar PV Power Calculations

To determine mathematically the electrical power acquired from the solar PV module, the following equation is studied in [18], [19]:

$$P = \eta_{sc}\tau_g\alpha_{sc}RA[1 - \mu_{sc}(T_{sc} - T_r)] \quad (1)$$

where,

$\eta_{sc}$: the reference efficiency of the solar PV cells
$\tau_g$: the glass transmissivity
$\alpha_{sc}$: the solar cell absorptivity
$R$: the solar radiation ($W/m^2$)
$A$: the total area of the solar cell ($m^2$)
$\mu_{sc}$: the thermal coefficient of solar PV cell efficiency (%/℃)
$T_{sc}$: the solar cell temperature (℃)
$T_r$: the reference temperature (℃)

By using the MLFFNN, the solar PV electrical power can be projected without using the previous equations and reliant on the solar PV system parameters, as discussed below.

## 3. MLFFNN Design, Training and Testing for Power Prediction

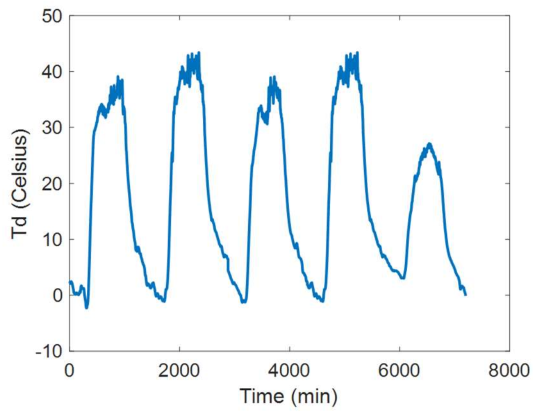
In this paper, MLFFNN is used to predict the power of the solar PV plant. MLFFNN is a very simple structure compared with the other types of NNs [12], [20], [21]. In addition, it can be easily and successfully applied in various problem domains [22]–[24]. The MLFFNN was proposed in [25]–[27] due to the properties of the adaptivity, parallelism, and generalization that it presents as well as it can be linear or nonlinear. MLFFNN requires a large number of pairs of input and target for the training process [28], [29], but this disadvantage is considered in the current work. In subsection 3.1, the proposed MLFFNN is designed. The training of the designed MLFFNN is presented in subsection 3.2.

### 3.1 MLFFNN Design

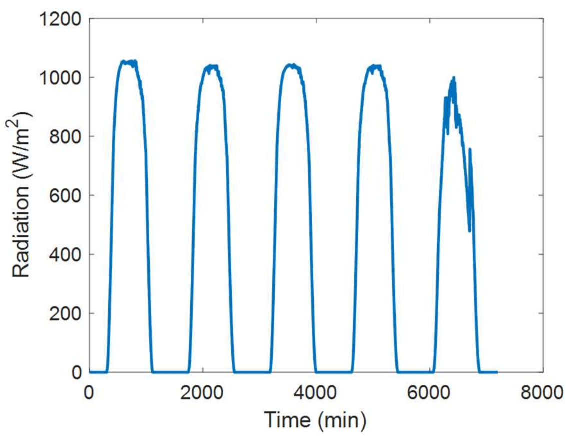
For the design of the MLFFNN, the main followed criteria [30]–[34] are that the inputs of the NN should achieve high performance; the lowest MSE and the lowest TE. After many trials and experiments, it is found that the main inputs that achieve the high performance for the MLFFNN are the difference between the module (cell) temperature and the reference temperature ($T_d = T_m - T_r$) and the solar radiation ($R$). The reference temperature $T_r$ is one of the PV module's properties and it is a constant value equal to $25^oC$ and it is abstracted from the module temperature based on the recommendation provided in ref. [19]. Fig. 2 represents these inputs to the MLFFNN.

The MLFFNN architecture composes of three layers; the input layer which contains the two inputs, the non-linear (hyperbolic tangent activation function) hidden layer, and the output layer which estimates the power of the PV power station $P'$. This estimated power is compared with the actual one obtained from a real PV power station $P$. This structure is presented in Fig. 3.

Moreover, the equations that represent the feedforward part of the designed MLFFNN are given as follows:




(a)




(b)

**Fig. 2** The inputs of the designed MLFFNN. (a) the temperature $T_d = T_m - T_r$ and (b) the solar radiation ($R$).

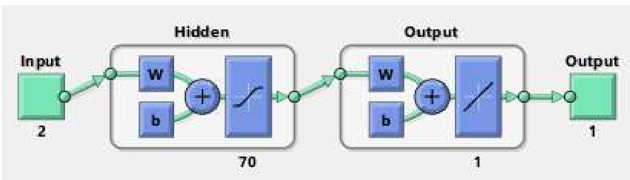



**Fig. 3** The designed MLFFNN structure. It is taken from MATLAB.

$$y_j = \varphi_j(h_j) = \varphi_j\left(\sum_{i=0}^{2} w_{ji}\, x_i\right) \quad (2)$$

where, $x_i$ are the inputs to the MLFFNN. $x_0 = 1$, $x_1 = T_d$, and $x_2 = R$. $y_j$ is the output of the hidden neuron $j$. $w_{ji}$ is the weight between the input $i$ and the hidden neuron $j$.

The activation function of the hidden layer is given by

$$\varphi_j(h_j) = \tanh(h_j) \quad (3)$$

The estimated power by the MLFFNN, $P'$, is given by

$$P' = \varphi_k(O) = \varphi_k\left(\sum_{j=0}^{n} b_{1j}\, y_j\right) = \left(\sum_{j=0}^{n} b_{1j}\, y_j\right) \quad (4)$$

where, $b_{1j}$ is the weight between the hidden neuron $j$ and the output of the MLFFNN which is the estimated power $P'$.

The power $P$ is used only for training the MLFFNN architecture and the training error $e(t)$ should be as small as possible and it is given by the following equation:

$$e(t) = P - P' \quad (5)$$

The training process of the designed MLFFNN is discussed in detail in the next subsection.

### 3.2 MLFFNN Training and Testing

In this subsection, the training process of the MLFFNN is presented in detail. For training the designed MLFFNN, Levenberg-Marquardt (LM) learning is used. LM algorithm can implement the work in a fast way. This algorithm is a type of second-order optimization technique that has a strong theoretical basis and provides significantly fast convergence and it is considered an approximation to Newton's Method [35], [36]. Compared with other learning algorithms, LM learning is applied because it has the trade-off between the fast learning speed of the classical Newton's method and the guaranteed convergence of the gradient descent [35], [37]. This learning is suitable for larger datasets as well as converges in fewer iterations and in a shorter time than the other training methods. The adjusted weights of the MLFFNN using LM algorithm are given by the following equation [12], [21]:

$$w_{k+1} = w_k - [\mathrm{H} + \lambda \mathrm{I}]^{-1} g \quad (6)$$

where, H and $g$ are Hessian and the gradient vector of the second order function respectively. I is the identity matrix of the same dimensions as H and $\lambda$ is a regularizing or loading parameter that forces the sum matrix $(\mathrm{H} + \lambda\mathrm{I})$ to be positive definite and safely well-conditioned throughout the computation.

The used data for training the MLFFNN are attained from a real PV power station in Egypt. The data for five days are used for training, whereas the data for the sixth day are used for checking the effectiveness of the trained MLFFNN. The total number of input-output pairs of the data used for training is 7200. From these data, 90% are used for the training process, 5% for validation, and 5% for testing. After trying many different weights' initializations and the number of hidden neurons, the best parameters of the MLFFNN that realize the high performance are as follows: the number of hidden neurons is 70, the number of iterations is 38, and the MSE is 0.034817. The training MSE of the MLFFNN is presented in Fig. 4 with the MSE being very low and close to the value of zero.

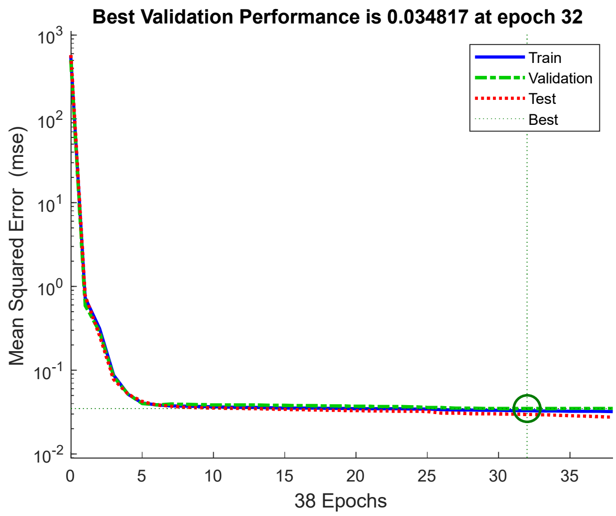



**Fig. 4** The lowest MSE obtained during the training of the designed MLFFNN.

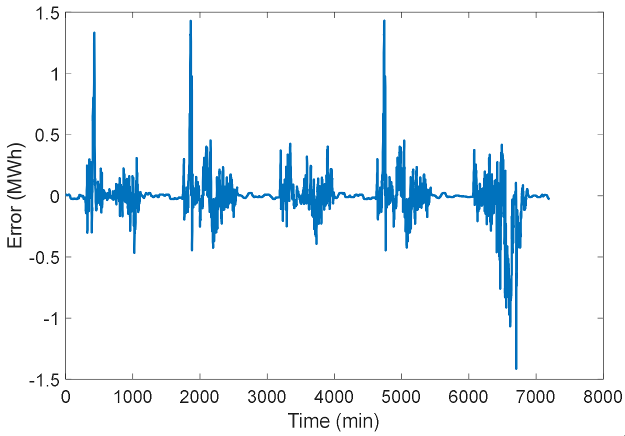



**Fig. 5** The approximation error between the estimated power $P'$ using the MLFFNN and the actual one $P$.

After the training of the MLFFNN is ended totally, the trained MLFFNN is tested and examined with the same dataset that was utilized for the training to get an insight into the approximation. The error between the estimated power by the MLFFNN $P'$ and the actual one obtained from a real PV power station $P$ is presented in Fig. 5.

As presented in Fig. 5, the approximation error between the estimated power by the MLFFNN and the actual power is low which means that the MLFFNN is trained very well. The average value of the absolute error is 0.0779 MWh which is low, and the standard deviation is 0.1812.

For more discussions, the estimated power by the MLFFNN and the actual one obtained from the real solar PV power station are compared. This comparison is presented in Fig. 6 which the convergence/approximation between the estimated power by the MLFFNN and the actual one is very good. This supports the results given in Fig. 5 and proves that the MLFFNN is trained very well.

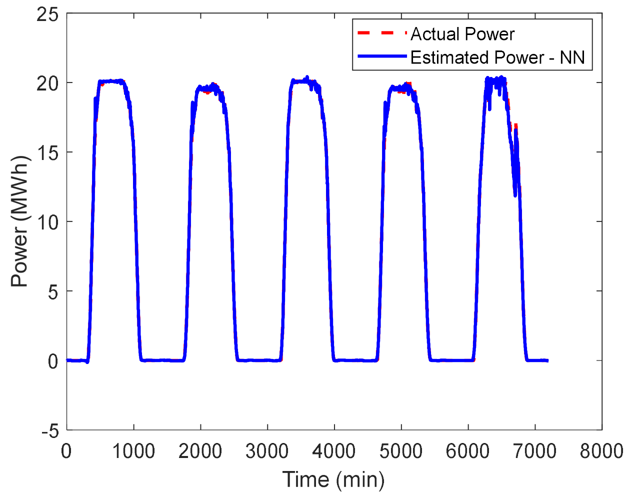



**Fig. 6** The comparison between the estimated power by MLFFNN and the actual one obtained from the real PV power station.

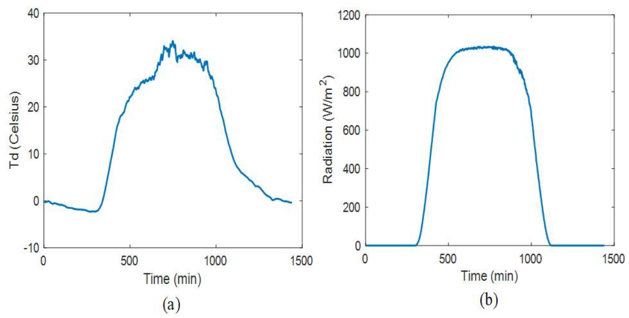



**Fig. 7** The data of the sixth day to check the effectiveness of the trained MLFFNN. (a) the temperature $T_d = T_m - T_r$ and (b) the solar radiation $(R)$.

## 4. Trained MLFFNN Effectiveness and Generalization

In this section, the trained MLFFNN is evaluated using different data than the data used for the training process. The data of the sixth day (the total number of input-output pairs is 1440) obtained from the real solar PV power station are used to test the effectiveness and the generalization ability of the trained MLFFNN. These data (temperature $T_d$ and radiation $R$) are presented in Fig. 7.

The comparisons between the estimated power by the trained MLFFNN and the actual one on the sixth day are presented in Fig. 8 and Fig. 9.

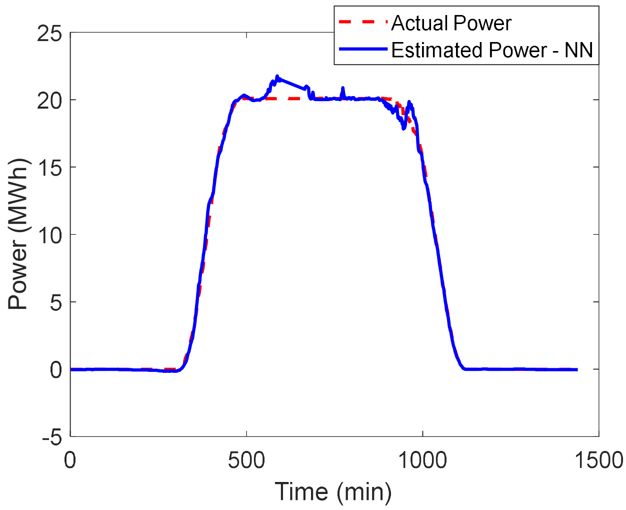



**Fig. 8** The comparison between the estimated power by trained MLFFNN and the actual one, using different data from the data used for the training process.

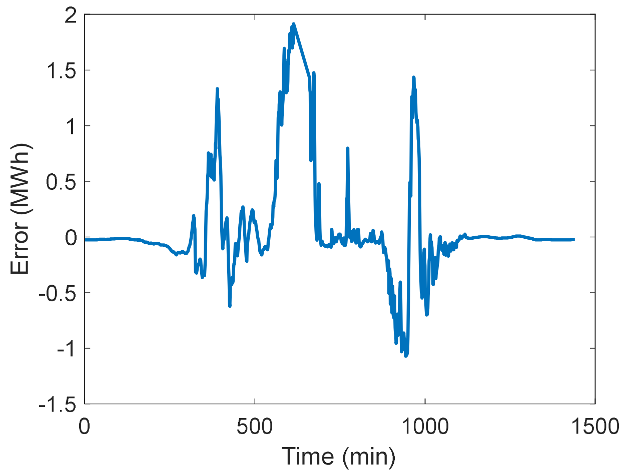



**Fig. 9** The error between the estimated power by trained MLFFNN and the actual one, using different data from the data used for the training process.

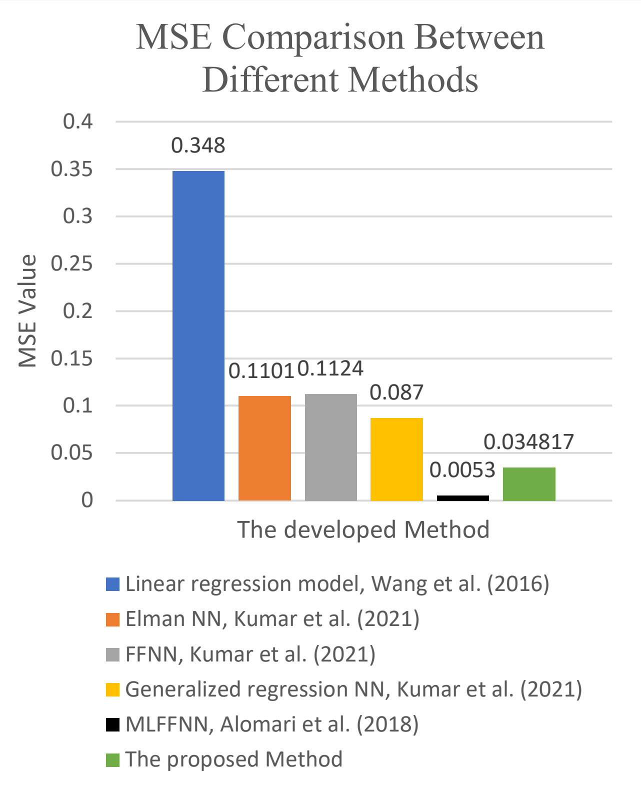



**Fig. 10** Comparing the resulted MSE from our proposed method with other previous published methods.

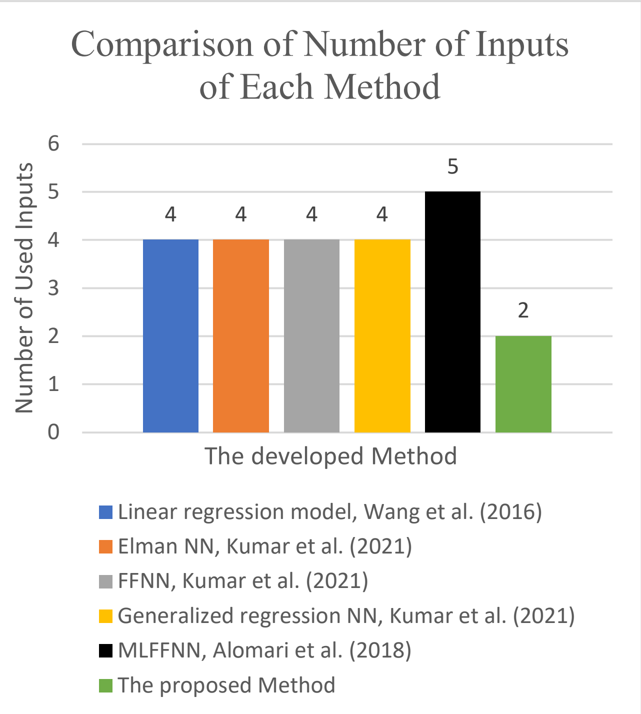



**Fig. 11** Comparing the number of the used inputs for our proposed method and other previous published methods.

As shown in Fig. 8 and Fig. 9 the error between the estimated power by the trained MLFFNN and the actual power is low, when different data is used than the training data. Indeed, this proves that the MLFFNN is trained very well. Furthermore, this proves that the trained MLFFNN can work and generalize well under different conditions and data than the ones used for training. From the results obtained in section 3 and 4, we conclude that the trained MLFFNN is efficient to predict the power correctly.

The proposed MLFFNN is compared with some other previous published methods which are used for the short-term power prediction and presented in ref. [11], [14], [16], [38]. This comparison is presented in Fig. 10 and Fig. 11, in terms of the resulted MSE and number of used inputs.

From Fig. 10, it is clear that our proposed method and the one presented in [16] achieve the lowest MSE compared with other methods. This means that our method and the one presented in [16] have the highest accuracy in predicting the solar PV output power. In Fig. 11, it is clear also that the number of inputs used with our method is the fewest compared with ones used with other methods. This prove that our method is the simplest. In addition, the calculations and the complexity are fewer. We found also that the generalization ability and the effectiveness under different conditions and cases are investigated and verified only with our proposed method.

## 5. Conclusion and Future Work

In this paper, a MLFFNN is proposed to predict the power for the solar PV power station. The temperature and radiation are its input, whereas the estimated power is its output. The data of the first five days are used for training. The training process leads to very low MSE and training error. This proves that the MLFFNN is trained well. The data of the sixth day, which are not used for the training, are used to check, and investigate the effectiveness of the trained MLFFNN. From this process, a low error is obtained between the estimated power by the trained MLFFNN and the actual power. This proves that the trained MLFFNN is working very well and efficient to predict the power correctly. In addition, the trained MLFFNN has the effectiveness and the generalization ability under different conditions and data. The correct power prediction using the trained MLFFNN can help to avoid the fall of the power that maybe happened in any time.

The proposed method is compared with other previous published ones. The result from this comparison reveals that the proposed method has the lowest MSE and number of used inputs. This means that the proposed method has the highest accuracy in predicting the solar PV output power. In addition, its complexity and calculations are fewer. Furthermore, we found that the generalization ability is checked and verified with the proposed method only.

The promising results in this paper motivate us, in the near future, to use and compare other different types of NNs for the prediction of the solar PV power. Deep learning also can be considered. In addition, the prediction horizon such as the medium-term and the long-term will be considered.

**Conflict of interest:** The authors state that there is no conflict of interest.

**Funding Acknowledgements:** The authors declare that no financial support has been received for this manuscript.

## References

[1] J. L. Gómez, A. O. Martínez, F. T. Pastoriza, L. F. Garrido, E. G. Álvarez, and J. A. O. García, "Photovoltaic power prediction using artificial neural networks and numerical weather data," *Sustain.*, vol. 12, no. 24, pp. 1–19, 2020. https://doi.org/10.3390/su122410295

[2] H. H. H. Mousa, A.-R. Youssef, and E. E. M. Mohamed, "State of the art perturb and observe MPPT algorithms based wind energy conversion systems: A technology review," *Int. J. Electr. Power Energy Syst.*, vol. 126, p. 106598, Mar. 2021. https://doi.org/10.1016/j.ijepes.2020.106598

[3] Z. A. Alrowaili *et al.*, "Robust adaptive HCS MPPT algorithm-based wind generation system using model reference adaptive control," *Sensors*, vol. 21, no. 15, pp. 1–20, 2021. https://doi.org/10.3390/s21155187

[4] M. M. Ali, A. R. Youssef, A. S. Ali, and G. T. Abdel-Jaber, "Variable step size PO MPPT algorithm using model reference adaptive control for optimal power extraction," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 1, pp. 1–21, 2020. https://doi.org/10.1002/2050-7038.12151

[5] S. K. Prajapati and K. B. Sahay, "A Survey Paper on Solar Irradiance Forecasting Methods," *Int. J. Eng. Res.*, vol. 5, no. 03, pp. 536–541, 2016. https://www.ijert.org/research/a-survey-paper-on-solar-irradiance-forecasting-methods-IJERTV5IS030469.pdf

[6] "In 2019 the solar PV market increased an estimated 12% to around 115 GW," 2020. [Online]. Available: https://www.evwind.es/2020/07/05/in-2019-the-solar-pv-market-increased-an-estimated-12-to-around-115-gw/75561

[7] C. Voyant *et al.*, "Machine learning methods for solar radiation forecasting: A review," *Renew. Energy*, vol. 105, pp. 569–582, 2017. https://doi.org/10.1016/j.renene.2016.12.095

[8] M. Q. Raza and A. Khosravi, "A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings," *Renew. Sustain. Energy Rev.*, vol. 50, pp. 1352–1372, 2015. https://doi.org/10.1016/j.rser.2015.04.065

[9] S. Sobri, S. Koohi-Kamali, and N. A. Rahim, "Solar photovoltaic generation forecasting methods: A review," *Energy Convers. Manag.*, vol. 156, pp. 459–497, 2018. https://doi.org/10.1016/j.enconman.2017.11.019

[10] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F. J. Martinez-de-Pison, and F. Antonanzas-Torres, "Review of photovoltaic power forecasting," *Sol. Energy*, vol. 136, pp. 78–111, 2016. https://doi.org/10.1016/j.solener.2016.06.069

[11] C. F. Yen, H. Y. Hsieh, K. W. Su, M. C. Yu, and J. S. Leu, "Solar Power Prediction via Support Vector Machine and Random Forest," *E3S Web Conf.*, vol. 69, no. 2, pp. 1–6, 2018. https://doi.org/10.1051/e3sconf/20186901004

[12] S. Haykin, *Neural Networks and Learning Machines*, Third Edit. Pearson, 2009. https://cours.etsmtl.ca/sys843/REFS/Books/ebook_Haykin09.pdf

[13] M. A. Nielsen, *Neural Networks and Deep Learning*. Determination Press, 2015. http://neuralnetworksanddeeplearning.com/

[14] P. M. Kumar, R. Saravanakumar, A. Karthick, and V. Mohanavel, "Artificial neural network-based output power prediction of grid-connected semitransparent photovoltaic system," *Environ. Sci. Pollut. Res.*, 2021. https://doi.org/10.1007/s11356-021-16398-6

[15] S. H. Oudjana, A. Hellal, and I. H. Mahamed, "Short term photovoltaic power generation forecasting using neural network," in *2012 11th International Conference on Environment and Electrical Engineering*, 2012, pp. 706–7011. https://doi.org/10.1109/EEEIC.2012.6221469

[16] M. H. Alomari, J. Adeeb, and O. Younis, "Solar photovoltaic power forecasting in Jordan using artificial neural networks," *Int. J. Electr. Comput. Eng.*, vol. 8, no. 1, pp. 497–504, 2018. http://doi.org/10.11591/ijece.v8i1.pp497-504

[17] M. AlShafeey and C. Csáki, "Evaluating neural network and linear regression photovoltaic power forecasting models based on different input methods," *Energy Reports*, vol. 7, pp. 7601–7614, 2021. https://doi.org/10.1016/j.egyr.2021.10.125

[18] A. Nahar, M. Hasanuzzaman, and N. A. Rahim, "Numerical and experimental investigation on the performance of a photovoltaic thermal collector with parallel plate flow channel under different operating conditions in Malaysia," *Sol. Energy*, vol. 144, pp. 517–528, 2017. https://doi.org/10.1016/j.solener.2017.01.041

[19] R. Nasrin, M. Hasanuzzaman, and N. A. Rahim, "Effect of high irradiation on photovoltaic power and energy," *Int. J. Energy Res.*, vol. 42, no. 3, pp. 1115–1131, 2018. https://doi.org/10.1002/er.3907

[20] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85–117, 2015. https://doi.org/10.1016/j.neunet.2014.09.003

[21] A.-N. Sharkawy, "Principle of Neural Network and Its Main Types: Review," *J. Adv. Appl. Comput. Math.*, vol. 7, pp. 8–

19, 2020. https://doi.org/10.15377/2409-5761.2020.07.2

[22] S. C. Chen, S. W. Lin, T. Y. Tseng, and H. C. Lin, "Optimization of back-propagation network using simulated annealing approach," in *2006 IEEE International Conference on Systems, Man and Cybernetics*, 2006, pp. 2819–2824. https://doi.org/10.1109/ICSMC.2006.385301

[23] M. A. Sassi, M. J. D. Otis, and A. Campeau-Lecours, "Active stability observer using artificial neural network for intuitive physical human–robot interaction," *Int. J. Adv. Robot. Syst.*, vol. 14, no. 4, pp. 1–16, 2017. https://doi.org/10.1177%2F1729881417727326

[24] E. De Momi, L. Kranendonk, M. Valenti, N. Enayati, and G. Ferrigno, "A Neural Network-Based Approach for Trajectory Planning in Robot–Human Handover Tasks," *Front. Robot. AI*, vol. 3, no. June, pp. 1–10, 2016. https://doi.org/10.3389/frobt.2016.00034

[25] A. B. Rad, T. W. Bui, V. Li, and Y. K. Wong, "A NEW ON-LINE PID TUNING METHOD USING NEURAL NETWORKS," *IFAC Proc. Vol. IFAC Work. Digit. Control Past, Present Futur. PID Control*, vol. 33, no. 4, pp. 443–448, 2000. https://doi.org/10.1016/S1474-6670(17)38283-6

[26] S. A. Elbelady, H. E. Fawaz, and A. M. A. Aziz, "Online Self Tuning PID Control Using Neural Network for Tracking Control of a Pneumatic Cylinder Using Pulse Width Modulation Piloted Digital Valves," *Int. J. Mech. Mechatronics Eng. IJMME-IJENS*, vol. 16, no. 3, pp. 123–136, 2016. http://ijens.org/Vol_16_I_03/163603-9898-IJMME-IJENS.pdf

[27] R. Hernández-Alvarado, L. G. García-Valdovinos, T. Salgado-Jiménez, A. Gómez-Espinosa, and F. Fonseca-Navarro, "Neural Network-Based Self-Tuning PID Control for Underwater Vehicles," *sensors*, vol. 16, no. 9: 1429, pp. 1–18, 2016. https://doi.org/10.3390/s16091429

[28] P. Jeatrakul and K. W. Wong, "Comparing the performance of different neural networks for binary classification problems," in *2009 8th International Symposium on Natural Language Processing, SNLP '09*, 2009, pp. 111–115. https://doi.org/10.1109/SNLP.2009.5340935

[29] D. Anderson and G. McNeill, "Artificial neural neworks technology: A DACS state-of-the-art report," Utica, New York, 1992. https://dokumen.tips/documents/artificial-neural-networks-technology-neural-networks-technology-a-dacs-state-of-the-art.html?page=2

[30] A.-N. Sharkawy and N. Aspragathos, "Human-Robot Collision Detection Based on Neural Networks," *Int. J. Mech. Eng. Robot. Res.*, vol. 7, no. 2, pp. 150–157, 2018. https://doi.org/10.18178/IJMERR.7.2.150-157

[31] A.-N. Sharkawy, P. N. Koustoumpardis, and N. Aspragathos, "Manipulator Collision Detection and Collided Link Identification based on Neural Networks," in *Advances in Service and Industrial Robotics. RAAD 2018. Mechanisms and Machine Science*, A. Nikos, K. Panagiotis, and M. Vassilis, Eds. Springer, Cham, 2018, pp. 3–12. https://doi.org/10.1007/978-3-030-00232-9_1

[32] A. N. Sharkawy, P. N. Koustoumpardis, and N. Aspragathos, "Neural Network Design for Manipulator Collision Detection Based only on the Joint Position Sensors," *Robotica*, vol. 38, no. Special Issue 10: Human–Robot Interaction (HRI), pp. 1737–1755, 2020. https://doi.org/10.1017/S0263574719000985

[33] A. N. Sharkawy, P. N. Koustoumpardis, and N. Aspragathos, "Human–robot collisions detection for safe human–robot interaction using one multi-input–output neural network," *Soft Comput.*, vol. 24, no. 9, pp. 6687–6719, 2020. https://doi.org/10.1007/s00500-019-04306-7

[34] A. N. Sharkawy and A. A. Mostfa, "Neural networks' design and training for safe human-robot cooperation," *J. King Saud Univ. - Eng. Sci.*, pp. 1–15, 2021. https://doi.org/10.1016/j.jksues.2021.02.004

[35] K. Du and M. N. S. Swamy, *Neural Networks and Statistical Learning*. Springer, 2014. https://doi.org/10.1007/978-1-4471-7452-3

[36] D. W. Marquardt, "An Algorithm for Least-Squares Estimation of Nonlinear Parameters," *J. Soc. Ind. Appl. Math.*, vol. 11, no. 2, pp. 431–441, 1963. https://doi.org/10.1137/0111030

[37] M. T. Hagan and M. B. Menhaj, "Training Feedforward Networks with the Marquardt Algorithm," *IEEE Trans. NEURAL NETWORKS*, vol. 5, no. 6, pp. 2–6, 1994. https://doi.org/10.1109/72.329697

[38] G. Wang, Y. Su, and L. Shu, "One-day-ahead daily power forecasting of photovoltaic systems based on partial functional linear regression models," *Renew. Energy*, vol. 96, pp. 469–478, 2016. https://doi.org/10.1016/j.renene.2016.04.089