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Adaptive neuro-fuzzy inference system for DC power forecasting for grid-connected PV system in Sharjah

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Abstract. Solar energy forecasting is essential to maintain PV system's performance in uncertain environmental conditions. Factors such as module temperature, ambient temperature, solar irradiance, and wind speed contribute to the DC current generated by PV systems. In this study, an adaptive neuro-fuzzy inference system (ANFIS) is developed on MATLAB to study a 2.88 kW grid-connected PV system in the harsh weather conditions of Sharjah. Solar irradiance, ambient temperature, module temperature, and wind speed are considered as the input membership functions in the developed ANFIS model. The output parameter considered in this study is the current DC generation, which critically depends on the defined membership functions. The accuracy of the model was determined based on the comparison with the experimental dataset. The R^2 value has shown that the proposed model can forecast the DC current with minimal error, with a value of 99.12% and 99.13% for training and testing, respectively. Moreover, the spatial 3-D surface has shown that the optimum DC current generation is achieved at the highest solar irradiance and ambient temperature while minimizing the module temperature for enhanced electrical efficiency.

Introduction

Conventional energy resources have been the main contributors to global warming and climate change, leading to the integration of clean energy sources [1]. Solar emissions received yearly present a huge portion of clean energy resources, making solar energy a remarkable source of alternate energy [2]. Photovoltaic (PV) systems have been designed to utilize solar emissions for clean electricity generation, therefore reducing carbon emissions and maintaining a clean economy [3].

Renewable Energy Sources (RES) have been increasingly integrated into the energy mix, specifically in oil-dependent countries such as the United Arab Emirates [4]. Moreover, solar irradiance exposure globally counts to 1367 W/m^2, which is sufficient to meet the electrical energy demand requirements worldwide [5,6].

However, to successfully integrate solar energy within the energy mix and attain electricity demands, its accurate prediction is necessary to ensure stability in power generation and injection into the energy grid [7,8]. Power generation from PV plants is known to be dynamic due to weather

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conditions dependency, presenting potential effects in its coupling with electrical networks [9]. In this notion, it's essential to forecast PV power plant generation to boost solar energy use and maintain electrical network stability. In principle, forecasting based on time-series data is extracted based on numerous amounts of sensors, guaranteeing precise data production and interval-based data measurement [10].

The accurate prediction of PV plants' performance is a critical task since weather conditions drive the operating conditions of PV plants. The dynamic change in solar irradiance causes fluctuation in PV power generation, leading to inconsistent electricity production. Multiple forecasting models are proposed to accurately predict PV plant generation [11]. Precise prediction of DC power generation requires the employment of machine learning (ML) techniques to enable learning complex pattern recognition and regression analysis [12]. Multiple forecasting models have been developed in the scientific literature such as ARIMA [13], support vector regression (SVR) [14], artificial neural network (ANN) and ANN-based hybrid models [15], hybrid intelligent system (HIS), Convolutional Neural Networks (CNN) [16], Long Short-Term Memory (LSTM) [17], and numerous other forecasting models.

The amalgamation of more than one forecasting offers an efficient compromise between prediction accuracy, computation time, and direct forecasting of PV plant power generation. Recently, ANN has been designed and modeled using a Fuzzy Inference System to develop an Adaptive Neuro Fuzzy Inference System (ANFIS) [18]. ANFIS and Support Vector Machine (SVM) have been popular tools for forecasting techniques and applications. However, ANFIS has proven to be precise as compared to SVM. Several studies discussed the employment of ANFIS in many fields of sciences [19,20], and as a model for accurate PV plant generation forecasting, proving its feasibility [21].

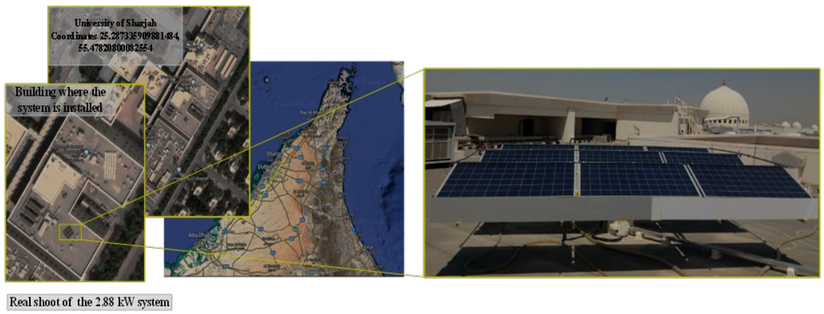
In this study, ANFIS has been employed to predict the performance of a 2.88 kW on-grid PV system installed in the terrestrial conditions of Sharjah, UAE. The forecasting of DC current is considered the main factor affecting PV power generation and therefore is considered in this study. Moreover, the relationship between the DC current and environmental factors such as solar irradiance, ambient temperature, module temperature, and wind speed is established. Therefore, the forecasting results are compared with the experimental results measured by the system to demonstrate the accuracy of the proposed model.

Experimental Setup

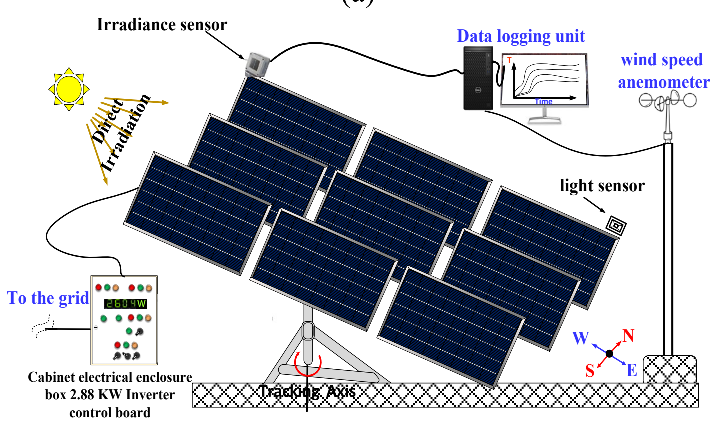
As seen in Fig. 1, a 2.88 kW on-grid photovoltaic system is installed on the rooftop of the W-12 central laboratories building at the University of Sharjah's main campus (Lat. 25.34° N; Long. 55.42° E) [22,23]. For immediate access to system data, the system is powered by a real-time data capture system [24]. The system's potential to function over short and long-time spans, together with its comprehensive infrastructure and improved data recording capabilities, were previously highlighted [25,26]. Furthermore, the system functions as a comprehensive grid-connected photovoltaic system, contributing AC electrical energy to the three-phase local utility grid. In addition, the on-grid photovoltaic system logs environmental and electrical characteristics every five minutes [27]. Table 1 represents the technical specifications of the on-grid PV system state-of-the-art.

Table 1. Technical Specifications of the 2.88 kW on-grid PV system

Equipment	Specifications
On-grid PV system State-of-the-Art	- 9 PV modules of 320 W electrical capacity. - Single Axis azimuth tracking. - 3.7 kWac Grid Inverter for Electrical Network Coupling and Synchronization. - Data manager for centralization system measurements on a common online interface.
Sensor Box	Responsible for coupling environmental sensors such as: - PT1000 thermocouples for module and ambient temperature measurement. - Irradiation sensor for solar insolation measurement. - Anemometer for wind speed measurement.



(a)



(b)

Fig 1. Illustration of 2.88 kW on-grid PV system (a) experimental setup (b) system visualization.

Adaptive network-based fuzzy inference system (ANFIS)

Deployment of fuzzy logic (FL) in control research has grown daily since the 1960s. The FL's foundation is expanding the well-known Boolean logic operations. The Fl employs binary systems (0 and 1) during the modeling procedure. Moreover, FL deals with multi-valued interpretation, which ranges from 0 to 1, just like in human perception. In the 1990s of this centuries, Jang created an Adaptive Network-based Fuzzy Inference System (ANFIS) based on the artificial neural network (ANN) and the fuzzy inference system (FIS) [28]. ANFIS can demonstrate a complicated system with extreme nonlinearity. The FL structure consists of three primary components: defuzzification, inference, and fuzzification.

In ANFIS, two different kinds of structures are combined to produce a fuzzy rule. The first kind is called Mamdani, and it was established in 1975 for the controller layout of heat transfer techniques where the Center of Gravity (COG) is the best defuzzifier. The second type, Sugeno (TSK), uses Weighted Average (Wtaver) as a defuzzifier. Eqs. (1) and (2) illustrate how these two types differ for fuzzy systems with two inputs and one output.

Should A be MF_A and B be MF_B, then C is the MF_C Mamdani form. (1)

In the event when A is MF_A and B is MF_B, C= F (A, B) Form of Sugeno (2)

MF_A and MF_B represent fuzzy membership functions (MFs) for A and B, respectively. A and B are the two input (antecedent) fuzzy systems. The membership functions for the Mamdani form are MFC, the membership functions for the Sugeno form are F (A, B), and the output (consequence) fuzzy system is C. For A and B as input factors, F (A, B) can be either a linear or nonlinear function [29].

In this study, since DC current generated from PV systems is critically dependent on several environmental factors such as solar irradiance, ambient temperature, and module temperature, the compound Sugeno form (TSK) model is considered to represent a nonlinear function and is studied. The phases of fuzzification and defuzzification were translated using the membership functions, respectively. To carry out this translation, the input and output values were converted from crisp to fuzzy during the fuzzification stage and from fuzzy to crisp during the defuzzification step.

The study's data was used to extract the rules. As indicated by Eq. 3, the total output value was computed using the number of input variables and the quantification of rules implemented.

$$y(x) = \frac{\sum_{i=1}^{n} w_i y_i(x)}{\sum_{i=1}^{n} w_i} \quad (3)$$

where the i_{th} fuzzy rule's weight, input, and output are represented by the variables y_i, x, and w_i, respectively. The weight of the ith fired rule has a range of [0 1].

A dataset of experimental measurements is used for the training and testing phases of 601 data points. With four input parameters, training and testing data were done for every fuzzy model output. Table 2 demonstrates every detail of the fuzzy model that was used in this investigation.

Table 2. Specifications of the developed fuzzy model

Fuzzy component	Type	Details
Inputs	Variables	4
Epochs	Number of Training Data	410
	Number of Testing Data	191
Rule	Number	4
	Base builder	SC
	ANDing Operation	Product
	ORing Operation	Probabilistic OR
	Implication	Min
	Aggregation	Max
	Defuzzification	Wtaver
Output	Function	Linear

Results and Discussion

A large data set of experimental data was employed for the developed ANFIS model. The prediction of DC current by the ANFIS model under the terrestrial conditions of Sharjah during harsh weather conditions is demonstrated in Fig 3. Moreover, the accuracy and precision of the proposed model according to the R^2 value, as presented in Fig 3, represent 99.1% accuracy. The ANFIS model can sufficiently forecast the DC current with respect to the experimental data that is measured from the system, as presented in Fig 2 and Fig 3.

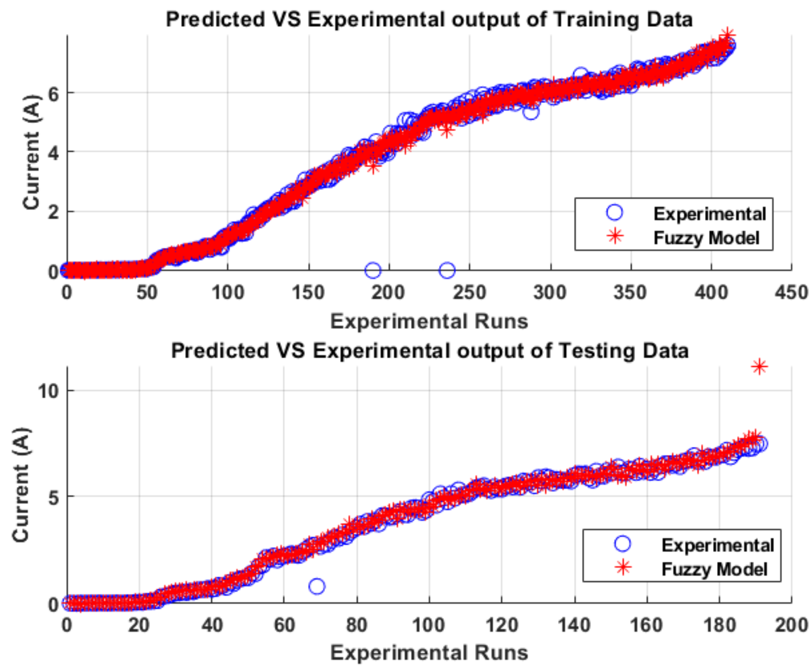


Fig 2. ANFIS model predictions for training and testing datasets for the experimental data.

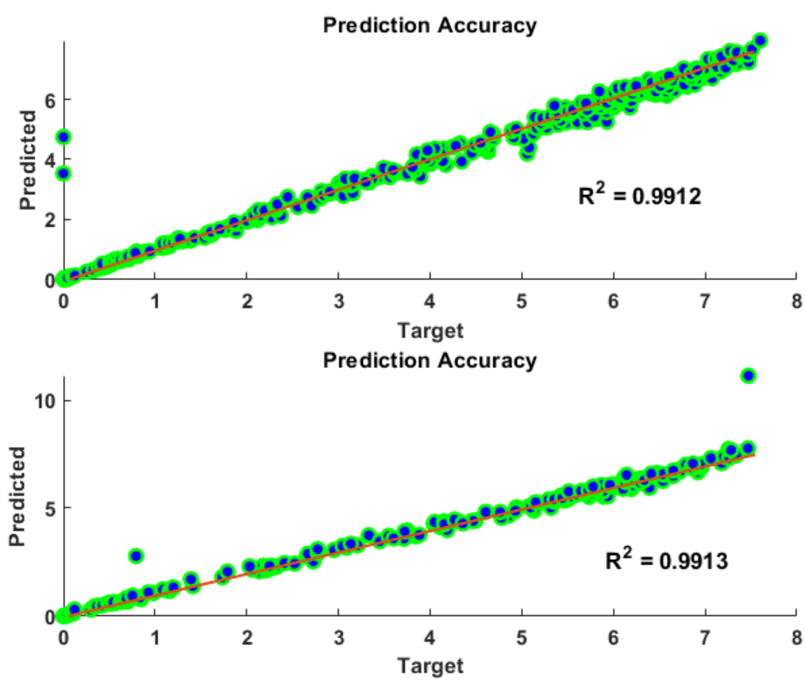


*Fig 3. Forecasting accuracy for training data **(above)** and testing data **(below)**.*

The input parameter membership functions that are employed in this investigation are presented in Fig 4. These functions are typically used as rules to convert between the fuzzification and defuzzification procedures. The different colors represent the various membership functions that are utilized to connect the fuzzification and defuzzification procedures within the fuzzy inference system architecture.

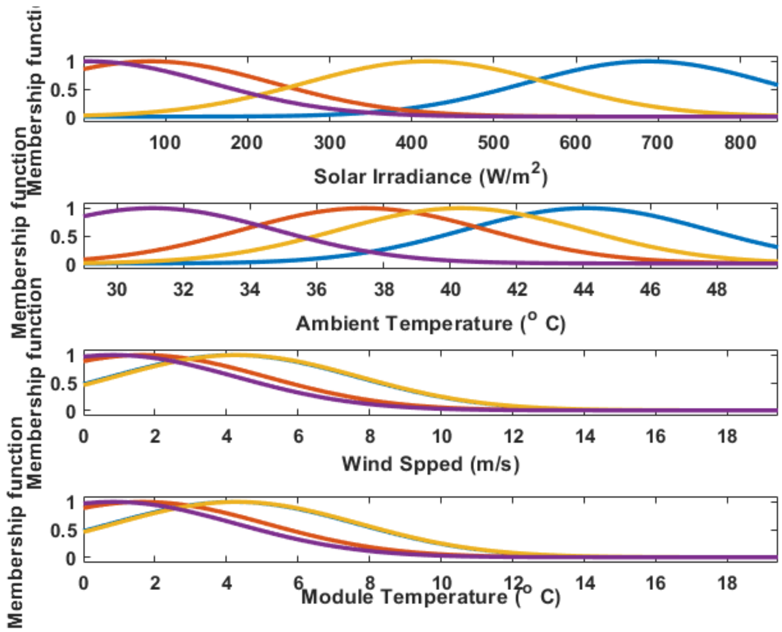


Fig 4. Membership Functions for input parameters for the developed ANFIS model.

Figs. 5 (a)-(e) represent the spatial 3-D surface for the DC Current (A) for the given PV system for each combination of the input parameters of the developed fuzzy model. The effect of ambient temperature, module temperature, and solar irradiance on the DC current generation is demonstrated in Fig. 5 (a) and (b), respectively. A direct relationship is observed with respect to ambient temperature and solar irradiance on the DC current generation. However, as module temperature increases significantly, the DC current is observed to reduce due to the reduction in the overall electrical efficiency of the system.

Moreover, Fig. 5 (c) depicts the impact of wind speed and ambient temperature on DC current generation. The spatial 3-D surface further demonstrates the direct relation of ambient temperature with DC current generation, while wind speed does not influence the DC current generation much.

Moreover, Figs. 5 (d) and (e) demonstrate the adverse impact of module temperature on the DC current generation as it increases significantly. The relative decrement in module temperature and maximizing the ambient temperature demonstrates an increase in the DC current generation as observed in Fig 5 (d). Furthermore, the minimal effect of wind speed on the DC current generation further confirms the findings presented in Fig 5 (c).

Therefore, the developed ANFIS model has demonstrated the performance of the demonstrated PV system based on four input variables. The DC current generation yield is at its highest when ambient temperature and solar irradiance are maintained at peak, while module temperature is minimized to attain maximum yield. This demonstrates the importance of incorporating cooling techniques to improve the PV system's electrical yield, sustaining its performance under harsh weather conditions.

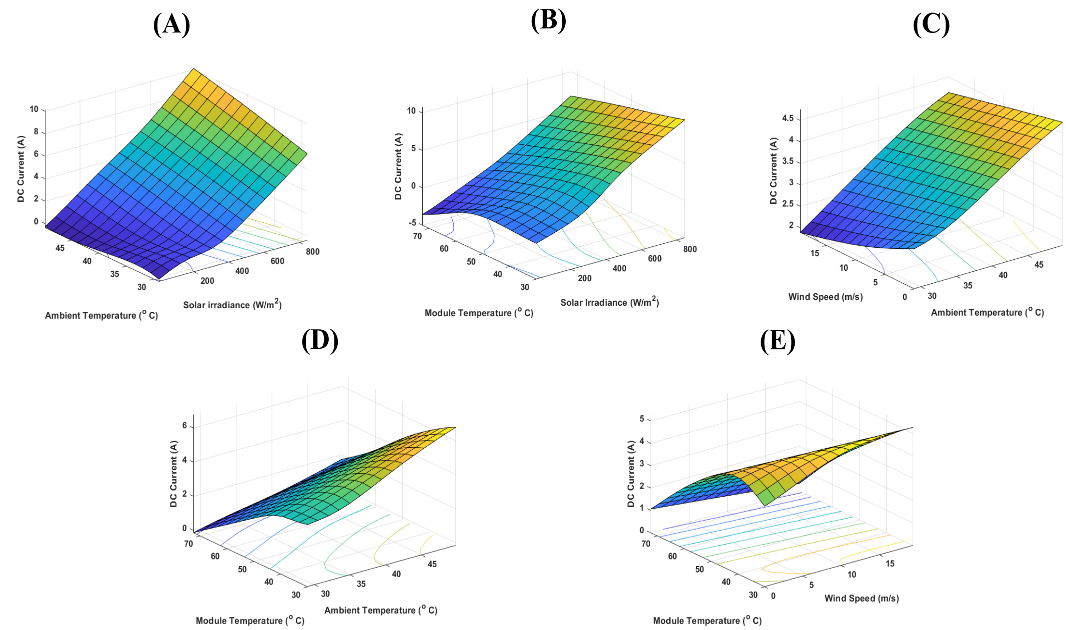


Fig 5. Spatial 3-D surface representation of DC current with respect to membership functions

Summary

PV System's DC current generation is affected by several environmental factors such as module temperature, ambient temperature, solar irradiance, and wind speed. In this study, the Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed to forecast the performance of a 2.88 kW on-grid PV system in the terrestrial conditions of Sharjah, UAE. The model adopted four input membership functions that relate to the DC current output power generation. DC current generation has observed a direct proportional relationship with respect to solar irradiance and ambient temperature, while module temperature presents an indirect relationship. This presents that DC current is improved at lower module temperatures while maintaining high solar irradiance exposure to enhance the electrical efficiency of the PV system. Moreover, the model presented a notable prediction accuracy and a significant correlation based on the least error, as the R^2 value corresponded to 99.12% and 99.13% for training and testing, respectively. Optimization techniques will be incorporated and tested in future work to improve the forecasting accuracy for larger datasets.

References

[1] J.L. Holechek, H.M.E. Geli, M.N. Sawalhah, R. Valdez, A Global Assessment: Can Renewable Energy Replace Fossil Fuels by 2050?, Sustainability. 14 (2022) 4792. https://doi.org/10.3390/su14084792

[2] T. Güney, Solar energy, governance and CO2 emissions, Renew. Energy. 184 (2022) 791–798. https://doi.org/10.1016/j.renene.2021.11.124

[3] A. Mehmood, J. Ren, L. Zhang, Achieving energy sustainability by using solar PV: System modelling and comprehensive techno-economic-environmental analysis, Energy Strateg. Rev. 49 (2023) 101126. https://doi.org/10.1016/j.esr.2023.101126

[4] M.M. Farag, R.C. Bansal, Solar energy development in the GCC region – a review on recent progress and opportunities, Int. J. Model. Simul. 43 (2023) 579–599. https://doi.org/10.1080/02286203.2022.2105785

[5] M. Jamei, M. Karbasi, M. Ali, A. Malik, X. Chu, Z.M. Yaseen, A novel global solar exposure forecasting model based on air temperature: Designing a new multi-processing ensemble deep learning paradigm, Expert Syst. Appl. 222 (2023) 119811.

https://doi.org/10.1016/j.eswa.2023.119811

[6] M.M. Farag, A.K. Hamid, T. Salameh, E.M. Abo-Zahhad, M. AlMallahi, M. Elgendi, ENVIRONMENTAL, ECONOMIC, AND DEGRADATION ASSESSMENT FOR A 2.88 KW GRID-CONNECTED PV SYSTEM UNDER SHARJAH WEATHER CONDITIONS, in: 50th Int. Conf. Comput. Ind. Eng., 2023: pp. 1722–1731.

[7] C. Scott, M. Ahsan, A. Albarbar, Machine learning for forecasting a photovoltaic (PV) generation system, Energy. 278 (2023) 127807. https://doi.org/10.1016/j.energy.2023.127807

[8] U.K. Das, K.S. Tey, M. Seyedmahmoudian, S. Mekhilef, M.Y.I. Idris, W. Van Deventer, B. Horan, A. Stojcevski, Forecasting of photovoltaic power generation and model optimization: A review, Renew. Sustain. Energy Rev. 81 (2018) 912–928. https://doi.org/10.1016/j.rser.2017.08.017

[9] M.M. Farag, N. Patel, A.-K. Hamid, A.A. Adam, R.C. Bansal, M. Bettayeb, A. Mehiri, An Optimized Fractional Nonlinear Synergic Controller for Maximum Power Point Tracking of Photovoltaic Array Under Abrupt Irradiance Change, IEEE J. Photovoltaics. 13 (2023) 305–314. https://doi.org/10.1109/JPHOTOV.2023.3236808

[10] E. Kim, M.S. Akhtar, O.-B. Yang, Designing solar power generation output forecasting methods using time series algorithms, Electr. Power Syst. Res. 216 (2023) 109073. https://doi.org/10.1016/j.epsr.2022.109073

[11] A. Alcañiz, D. Grzebyk, H. Ziar, O. Isabella, Trends and gaps in photovoltaic power forecasting with machine learning, Energy Reports. 9 (2023) 447–471. https://doi.org/10.1016/j.egyr.2022.11.208

[12] F. Pereira, C. Silva, Machine learning for monitoring and classification in inverters from solar photovoltaic energy plants, Sol. Compass. 9 (2024) 100066. https://doi.org/10.1016/j.solcom.2023.100066

[13] Y. Chen, M.S. Bhutta, M. Abubakar, D. Xiao, F.M. Almasoudi, H. Naeem, M. Faheem, Evaluation of Machine Learning Models for Smart Grid Parameters: Performance Analysis of ARIMA and Bi-LSTM, Sustainability. 15 (2023) 8555. https://doi.org/10.3390/su15118555

[14] M. Jobayer, M.A.H. Shaikat, M. Naimur Rashid, M.R. Hasan, A systematic review on predicting PV system parameters using machine learning, Heliyon. 9 (2023) e16815. https://doi.org/10.1016/j.heliyon.2023.e16815

[15] S. Pereira, P. Canhoto, R. Salgado, Development and assessment of artificial neural network models for direct normal solar irradiance forecasting using operational numerical weather prediction data, Energy AI. 15 (2024) 100314. https://doi.org/10.1016/j.egyai.2023.100314

[16] S.B. Bashir, M.M. Farag, A.K. Hamid, A.A. Adam, A.G. Abo-Khalil, R. Bansal, A Novel Hybrid CNN-XGBoost Model for Photovoltaic System Power Forecasting, in: 2024 6th Int. Youth Conf. Radio Electron. Electr. Power Eng., 2024. https://doi.org/10.1109/REEPE60449.2024.10479878

[17] M.S. Ibrahim, S.M. Gharghory, H.A. Kamal, A hybrid model of CNN and LSTM autoencoder-based short-term PV power generation forecasting, Electr. Eng. (2024). https://doi.org/10.1007/s00202-023-02220-8

[18] G. Perveen, M. Rizwan, N. Goel, An ANFIS-based model for solar energy forecasting and its smart grid application, Eng. Reports. 1 (2019). https://doi.org/10.1002/eng2.12070

[19] T.M.M. Abdellatief, M.A. Ershov, V.M. Kapustin, E.A. Chernysheva, V.D. Savelenko, T. Salameh, M.A. Abdelkareem, A.G. Olabi, Uniqueness technique for introducing high octane environmental gasoline using renewable oxygenates and its formulation on Fuzzy modeling, Sci. Total Environ. 802 (2022) 149863. https://doi.org/10.1016/j.scitotenv.2021.149863

[20] T.M.M. Abdellatief, M.A. Ershov, V.M. Kapustin, E.A. Chernysheva, V.D. Savelenko, T. Salameh, M.A. Abdelkareem, A.G. Olabi, Novel promising octane hyperboosting using isoolefinic gasoline additives and its application on fuzzy modeling, Int. J. Hydrogen Energy. 47 (2022) 4932–4942. https://doi.org/10.1016/j.ijhydene.2021.11.114

[21] T. Salameh, E.T. Sayed, A.G. Olabi, I.I. Hdaib, Y. Allan, M. Alkasrawi, M.A. Abdelkareem, Adaptive Network Fuzzy Inference System and Particle Swarm Optimization of Biohydrogen Production Process, Fermentation. 8 (2022) 483. https://doi.org/10.3390/fermentation8100483

[22] M.M. Farag, F.F. Ahmad, A.K. Hamid, C. Ghenai, M. Bettayeb, M. Alchadirchy, Performance Assessment of a Hybrid PV/T system during Winter Season under Sharjah Climate, in: 2021 Int. Conf. Electr. Comput. Commun. Mechatronics Eng., IEEE, 2021: pp. 1–5. https://doi.org/10.1109/ICECCME52200.2021.9590896

[23] F.F. Ahmad, M. Abdelsalam, A.K. Hamid, C. Ghenai, W. Obaid, M. Bettayeb, Experimental Validation of PVSYST Simulation for Fix Oriented and Azimuth Tracking Solar PV System, in: 2020: pp. 227–235. https://doi.org/10.1007/978-981-15-4775-1_25

[24] M.M. Farag, F.F. Ahmad, A.K. Hamid, C. Ghenai, M. Bettayeb, Real-Time Monitoring and Performance Harvesting for Grid-Connected PV System - A Case in Sharjah, in: 2021 14th Int. Conf. Dev. ESystems Eng., IEEE, 2021: pp. 241–245. https://doi.org/10.1109/DeSE54285.2021.9719385

[25] T. Salameh, A.K. Hamid, M.M. Farag, E.M. Abo-Zahhad, Energy and exergy assessment for a University of Sharjah's PV grid-connected system based on experimental for harsh terrestrial conditions, Energy Reports. 9 (2023) 345–353. https://doi.org/10.1016/j.egyr.2022.12.117

[26] T. Salameh, A.K. Hamid, M.M. Farag, E.M. Abo-Zahhad, Experimental and numerical simulation of a 2.88 kW PV grid-connected system under the terrestrial conditions of Sharjah city, Energy Reports. 9 (2023) 320–327. https://doi.org/10.1016/j.egyr.2022.12.115

[27] M.M. Farag, A.K. Hamid, Experimental Investigation on the Annual Performance of an Actively Monitored 2.88 kW Grid-Connected PV System in Sharjah, UAE, in: 2023 Adv. Sci. Eng. Technol. Int. Conf., IEEE, 2023: pp. 1–6. https://doi.org/10.1109/ASET56582.2023.10180880

[28] J.-S.R. Jang, ANFIS: adaptive-network-based fuzzy inference system, IEEE Trans. Syst. Man. Cybern. 23 (1993) 665–685. https://doi.org/10.1109/21.256541

[29] T. Salameh, P.P. Kumar, E.T. Sayed, M.A. Abdelkareem, H. Rezk, A.G. Olabi, Fuzzy modeling and particle swarm optimization of Al2O3/SiO2 nanofluid, Int. J. Thermofluids. 10 (2021) 100084. https://doi.org/10.1016/j.ijft.2021.100084