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Predicting Solar Power Generation Utilized in Iraq Power Grid Using Neural Network

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Abstract: The prediction of a photovoltaic (PV) energy production over time is considered the major challenge to integrate it with the utilized grid. This is because it is affected by many factors, including geographical locations and weather conditions. Hence, accurately forecasting PV generation is crucial for ensuring grid stability. In this paper, several studies are discussed between 2015 to 2023 based on various term forecasting conditions. Then, a neural network (NN) is employed to forecast a medium-term PV power generation by gathering meteorological data specific to the Misan Governorate in the southern region of Iraq. The proposed NN model based on Python language is trained to find the PV power prediction for various seasons of the year using solar radiation and surrounding temperature of weather condition tests. At the same time, the MATLAB Simulink model is designed to address the PV actual power for the same tests. Finally, various statistical measures were introduced to assess the network's performance, including RMSE, MSE, R2, and MAE. The results demonstrate that the model can predict accurately, with an RMSE value of 0.092785 kW in September, which is 39.1% lower than in January, 34.14% lower than in March, and 22.022% lower than in July. Overall, this study contributes to the advancement of solar power forecasting techniques and highlights the potential of NN in optimizing renewable energy integration into the grid. The average power generated by the NN in the ninth month was approximately 565 watts, closely resembling the actual value of 574 watts.

Keywords: Photovoltaic Energy Source; Neural Network technique; Term-Forecasting Model; Prediction Test and Utilised Iraq-Grid

1. Introduction

In recent years, the global population has led to a surge in energy consumption, primarily from fossil fuels, which have negative environmental impacts due to CO2 emissions. This trend is further exacerbated by the finite nature of fossil fuels, and extraction is slow, making them unsustainable in the long term. Consequently, several studies have advocated adopting renewable energy sources, such as solar PV systems, to address future energy scarcity and mitigate these impacts. Additionally, PV systems provide clean and safe electricity, thereby facilitating that harmful emissions can be reduced, the environment protected, and sustainable development achieved [1]–[3]. Furthermore, several studies have indicated that the Earth's surface receives significant solar radiation, approximately 1.8×1011 MW, exceeding the world's electrical power demand[4].

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With that, the expansion of PV has obstacles, including the sporadic and unpredictable nature of energy production, which is impacted by meteorological factors such as solar radiation and cloud coverage[5]. Such circumstances can result in disparities within the PV system, thereby impacting the stability of the interconnected electrical grid. Due to the intermittent and uncontrollable nature of solar energy production, the accurate prediction of solar power generation is critical for both grid and operators. Where the main responsibility of the grid operator is to ensure a balance between supply and demand through electrocortical supply and demand planning because, If the energy demand is greater than the value of the energy generated, this leads to a decrease in the frequency and instability of the network and if this continues for some time leads to the interruption of the supply of parts of the electrical grid and therefore any unexpected difference in generation can lead to contract violations and significant financial losses. Hence, it is necessary to accurately predict solar power generation to prevent any fluctuations or interruptions in the supply and thus maintain the stability of the grid[6]. Possible remedies involve the utilization of a short-term predictive model. Where numerous methodologies have been examined to forecast PV energy generation through machine learning algorithms to mitigate these variations[7].

In previous literature, many models have been presented such as statistical, artificial intelligence, hybrid, and optimization methods. These models have greatly improved forecasting capabilities[8]. Where artificial Neural Network is extensively utilized due to its established efficacy over an extended period. The most effective results had been achieved by the types of NN technique; the ENN[9], RBFNN[10], DRNN[10], GRNN, and FFNN [11]. In addition, research on PV power production forecasting encompasses a range of methodologies, categorized as long-term, middle-term, and short-term forecasting based on the duration of the prediction this will be discussed later[12]. The majority of published research emphasizes the prediction of PV energy generation using solar radiation in different countries, whilst the Iraq region has not been addressed recently. Therefore, this study has discussed the proposal of a PV model to predict the production of PV energy using artificial intelligence, taking into account the meteorological parameters of the southern region of Iraq.

In this research, Misan Governorate in southern Iraq is employed as a case study for the first time to predict long-term PV power generation based on analyzing the effectiveness of an ANN using weather data sets. The model is trained based on Python language using solar irradiance and surrounding temperature of weather conditions to address the differences between actual and predicted power values quantifying the RMSE, MAE, and R2. Four months are selected based on various seasons of the year: January, March, June, and September. The results demonstrated the effectiveness of the NN in analyzing various weather data, particularly highlighting the superior energy production during September when the sky is predominantly clear. The rest of the paper is structured in the following stages: Section 2 examines the scientific literature of the last ten years. While Section 3 provides detailed information on solar panel specifications and attributes. In section 4, the ANN technique is explained in detail. Then, the methodology of collecting training data, data preparation, and modified technique is explained in Section 5. Next, Section 6 summarizes the outcomes obtained from the proposed model. Finally, Section 7 provides the conclusion of this research as well as it is referred to the future works.

2. State of arts utilizing PV prediction

The last studies highlight the importance of accurate forecasting for efficient utilization of PV energy, which is crucial for effective grid integration and energy management. They have explored techniques such as statistical models, machine learning algorithms, and hybrid approaches to improve forecasts. Weather conditions, historical data, and real-time measurements have all been considered to improve forecasting accuracy. Forecasting is divided into four categories based on the duration, and each prediction horizon has a specific use [13].

2.1 Very short-term forecasting

This part includes forecasting terms made based on a few seconds, several minutes to an hour in advance. To enhance the accuracy of the model, numerous academics have suggested a range of modifications; among them the authors in [14] created a hybrid model for forecasting PV energy production and WD with an ANN. The model used theoretical solar irradiance and meteorological data; the data was collected from the State Key Laboratory of Alternative Electric Energy Systems at North China Electric Power University. The hybrid model demonstrated improved predictive accuracy and faster convergence compared to the ANN method, with MAE values of 3.639%, 9.578%, and 10.349% for clear, cloudy, and rainy days. In the same way, the authors in [15] introduced a new method for predicting power output in PV systems using the CFS and machine learning algorithms. The model uses NN and SVR, with univariate and multivariate models based on past data. An extensive evaluation using 5-minute, two-year data from an Australian plant showed that the univariate model was the most accurate, with a mean relative error of 4.15–9.34%.

Next, the authors in [16] suggested a better way to predict solar energy using an ANN, fuzzy logic pre-processing, and an error correction factor. The model, trained using Singapore weather data from January to March 2017, showed a significant improvement of 29.6% in MAPE and consistently outperformed other models. In contrast, the authors in [17], proposed a short-term energy forecasting model for PV systems, incorporating environmental factors and support vector technology based on a grey correlation coefficient algorithm and GA optimization to improve accuracy. The GA-SVM model outperformed the SVM model in accuracy, with relative error values reaching 9.28% for sunny conditions and 11.04% for cloudy conditions. In 2018, the authors in [18] compared various methods for estimating hourly power generation from solar power plants using data from 32 plants in Italy, analyzing 24-hour forecasts of direct, diffuse, and total irradiance and temperature. They found that ENS, QRF, and KNN had superior performance, while SVR, ANN, and GB generally precise forecasts yielded less. The study [19] examines a forecasting model using an RNN and BPTT algorithm for adjacent days and within the same day, with forecasting horizons ranging from 15 to 90 minutes. The approach shows significant improvements in the MAE index and RMSE compared to other models, with MAPE improving by 66%, 56.80%, 32.88%, 42.94%, and 34.84%, respectively. While the authors in [20] used the ANFIS system to predict the power solar generation installed in Hermosillo, Sonora, and Mexico City. The model achieved a mean absolute error of 169.2W and a mean absolute percentage error of 5.8% for Hermosillo and 1.6% for Mexico City. Next, the author in [21] developed a new method for forecasting PV power output in Variable-Speed Turbine (VST) systems using data from the YULARA PV system in Alice Springs, Australia. The proposed model outperforms other methods, exhibiting a lower RMSE of 31.49% and a 2.152% higher R-squared value.

In 2020, the authors in [22] introduced an EMD method for predicting short-term PV power installed at the rooftop of SOA University in Bhubaneswar, Odisha, India. The proposed method achieved the best performance, with MAPE, RMSE, and MAE values reaching 0.0239, 1.8852, and 0.0189, respectively. Similarly, the authors in [23] studied how meteorological conditions affected performance requirements in a grid-connected PV facility for collected data from 2017–2018 in 15-minute intervals. The study shows that the proposed method achieved a coefficient of determination of over 0.99%. In the same way, the authors in [24] presented an accuracy of machine learning models for solar power modeling by leveraging data from January 2018 to June 2019 from Kookmin University and the Korea Meteorological Administration. Those machine learning models are evaluated in the study and are revealed as unbiased estimations with 0.96% and 0.03% MBD, respectively. In 2022, the scholar in [25] created a cloud-based forecasting tool for predicting PV system performance at the distribution level in DSO Cyprus using utility-scale operational data from four aggregation areas. This hybrid model output averaging approach was the most effective, achieving a mean absolute percentage error of 9.11%. To estimate the output power of the PV system, the authors in [26] employ a hybrid approach that combines ANN with VMD and external optimization approaches like ACO using hourly data from 2019 in Beijing, China. The results show that VMD-ACO-2NN performs better in prediction than other approaches, with low RMSE and high R2 values of 0.0232 and 0.9768, respectively. In the same year, the scholar in [27] investigated different machine learning models to study hourly solar irradiance and temperature data from 2016 to 2019 in Jubail Industrial City, Saudi Arabia. The kNN model was the most favorable, achieving MAE values of 0.0806, RMSE of 0.1868, n-RMSE of 0.132, and R2 of 0.99. In contrast, the authors in [28] combined a WNN and a GA technique to enhance the forecasting of PV power plant outputs. This study proves that the forecasts experienced a slight reduction in accuracy and stability on overcast and rainy days, with relative errors of 7.8% and 10.1%, respectively. In the same way, the authors in [29] explored an ANN framework for accurate predictions of sustainable energy resources, specifically wind and solar power. The results show that it is achieved a long-term prediction was achieved with a value of R2 about 0.9821.

In 2023, the authors of [30] explored deep learning algorithms for predicting solar power output in the Galapagos Islands of Ecuador using an optimized hyperparameter-based Bayesian optimization algorithm for data collected from 2018 to 2020. Results show that this hybrid method is highly effective in short-term PV power forecasting, with an excellent correlation coefficient of over 99%. Similarly, the authors in [31] evaluated the performance of regression models in for spatiotemporal projections using fifteen machine learning and deep learning algorithms in five cities in California from 2018 to 2020 within a 30-minute time frame. These proposed models displayed the highest accuracy, with GRU outperforming the LSTM with a consistent R2 score of 0.94.

2.2 Short-term forecasting

This part is designed for forecasting terms including predictions for the next one to three hours, one day, or one week in maximum. In 2014, the authors in [32] used statistical methodologies to predict the construction of a 960 kW PV plant in Italy for 365 days. The results show that the ANN with input vector III outperformed the forecasting system with a lower error rate of 10%, with input vectors I, II, and III ranging from 9.40% to 6.50%. In 2026, the authors in [33] developed a method for forecasting PV power using a Bayesian framework for data collected in three Italian PV farms. The study proves that the proposed method achieved a 94% cross-correlation coefficient and 7% root mean square error. While The study of [34] introduced used ANN for predicting a PV power in a Beijing, China smart microgrid using a Feed-forward NN to improve the MSE of the NN model from 8.8 to 8.2 present. Similarly, the authors in [35] offered a NNBP for predicting the power output of a PV system 24 hours in advance located in Ashland, Oregon. The results show that this proposed NN model revealed MAPE about 6.78%, 6.93%, 7.67%, and 7.27% For four distinct prediction days in 2013. During the same year, the authors in [36], employed the GLSSVM method as a time series forecasting tool that utilizes meteorological data obtained from the University of Salento to estimate PV power. The PCAWD technique outperforms PCA, WD, and WDPCA in hour-ahead forecasts, enhancing forecast accuracy by reducing mean error bias by up to 1%. In 2017, the scholars in [37] compared a self-organizing feature map-based mathematical model for energy output prediction in solar panels with existing models like MLP and SVM. It forecasted the efficiency of a PV system at Sohar University in Oman from July 2013 to August 2014 using data from solar irradiation and research laboratory production. The proposed model achieved a final MSE of 0.0001 in the training and cross-validation phases with a correlation factor of 0.9996 and a coefficient of determination R2 value of 0.9555.

In 2019, the authors in [38] introduced the GA-based SVM data PV system for 278 days. The model's accuracy was improved through optimization, resulting in an RMSE of 11.226 W and a MAPE of 1.7052 percent, compared to conventional SVM's higher RMSE and MAPE. In the same year, the authors [39] used a deep neural network model that used weather data to forecast the power production of PV systems located in Taiwan's solar dataset for 2015. the results show that the proposal performed better than other approaches in terms of MAE of 109.4845 and RMSE of 163.1513. Similarly, the scholars in [40] discussed advanced NN and machine learning-based PV power forecasting algorithms for data collected in a UK PV park from 2017 to 2018. The hybrid model achieved the best overall performance, with an annual n-RMSE of up to 6.74%. Consequently, the authors in [41], proposed a model using a random forest algorithm that predicts PV power generation in northern China during winter for six factors and categorizes winter days into clear, cloudy, and rainy/snowy days. The model and three alternative methods achieve an MAE of 5.07, MAPE of 2.83, RMSE of 6.23, and an EV of 0.95 for clear days. In the same design, the authors in [42], predicted the amount of electricity generated by a solar system at the University of Salento in Monteron-di-Lecce, Italy, using the NWP model for data collected from March 6, 2012, to December 30, 2013. This study demonstrated that n-RMSE values of 2.9% and 9.9% were reached in the corresponding circumstances. The study of [43] developed a hybrid deep neural network for weather forecasting using data from the Yeongam solar power plant in South Korea. The results showed that it had achieved an impressive R2 value of 92.7%. In the same way, the authors of [44] conducted a study in Brazil from 2007 to 2011, focusing on integrating and optimizing intermittent renewable energy sources. The collected solar radiation and wind speed data were analyzed using criteria like latent root, explained variance, and Bebel's test, and used Principal Components Analysis to compare outcomes. The study demonstrates the potential of optimizing renewable energy in electrical systems.

Next, the authors in [45] used the LSTM-GPR hybrid technique, for solar power predictions located at the University of Illinois dataset from 2016 to 2017. This hybrid model proves that MSE for LSTM_GPR of 9.43%, LSTM of 14.78%, and GPR of 10.64. In contrast, the authors in [46] presented a deep recurrent NN for predicting PV power output using historical data from a solar power facility in Nicosia, Cyprus, from September 2016 to January 2019. The model outperforms other methods like ANN, ANN2, DNN, LSTM2, and Arima and S-Arima, with an RMSE value of 0.11368 and a standard deviation of 0.01616 when using k-fold cross-validation. In 2021, the study of [47] evaluates day-ahead PV power production forecasting using machine learning techniques for data collected from a test-bench PV system in Nicosia, Cyprus. It was exhibiting the lowest forecasting errors with an n-RMSE of 4.53% and MAPE of 3.17%. In the same year, the authors of [48] developed two models; ANFIS-APSO and the other ANFIS-IPSO, using data from a 960 kW PV system at the University of Salento, Italy. The ANFIS-APSO model achieved the highest accuracy in predicting PV power during the testing phase for 12 and 24-hour lead times, with RMSE values of 0.088 kW and 0.081 kW and R2 values of 0.835 and 0.657, respectively. Similarly, the scholar of [49], presented an LM-BP neural network to test the historical data collected from the Jiaxing Power PV station. The model incorporated the similar hour approach and the LM-BP neural network, which showed a remarkable decline to below 10% during abrupt weather conditions.

In 2022, the authors of [50], developed a short-term PV power prediction model using EEMD-SSA-LSTM, a hybrid model combining various statistical methods. Data from a 100 MW PV power plant in Zhejiang Province, China, was collected in April 2017. The model was optimized for structural parameters and predicted results consistently above 98% in three typical weather scenarios, surpassing 99% accuracy on sunny days, demonstrating its superior prediction accuracy. In the same year, the author of [51] introduced a Stack-ETR algorithm to predict the power output of PV systems one day in advance. This prediction is achieved using three machine learning algorithms: random forest regression, extreme gradient boosting, and adaptive boosting. The data utilized in this research was collected from the Power Electronics and Renewable Energy Research Laboratory at the University of Malaya. The study results indicate that the Stack-ETR model outperforms other models by reducing the RMSE values to 36.95. Next, the authors in [52] developed a novel approach for efficient solar systems and precise prediction of PV power output, especially in partial shading scenarios, in Korea. The MLP artificial neural network processed and analyzed extensive datasets. The network was trained using the Levenberg-Marquardt algorithm, achieving a maximum MSE of 0.15, enabling more precise predictions even when radiation and temperature conditions varied.

2.3 Medium-term forecasting

This part of forecast predictions is made for one month to one year in advance. In 2020, a study conducted by [53], was referred that the parameters of an RBFNN model were changed using competitive swarm optimization for data collected from a Dutch village during; July, September, and December. The CSO-RBF model achieved remarkable average RMSE values of 0.003843, 0.004131, and 0.002846 for the summer, autumn, and winter seasons. Next, the authors in [54] used data from 1999 to 2020 to examine changes in solar radiation in the Canary Islands, Spain using a three-stage clustering procedure to examine temporal fluctuations, optimal combinations, and hierarchical clusters. The results show that significant monthly differences from annual averages were observed; January had a negative rate of 34.88%, February was 19.5%, and December was 40.31%. In the same way, the scholars in [55] examined the efficacy of deep learning methods in predicting PV power generation in Thailand for three months of data. This model proved that the quantified processing is 32.16 kW, 9.07%, and 72.56 kW in terms of MAE, MAPE, and RMSE, respectively. In the next year, the authors in [56] conducted in Brazil under the EOSOLAR project employed an AI-driven approach to assess the integration of hybrid systems with wind and solar grids. The study, which took place between November 2021 and November 2022, discovered that a GA could generate a 39% rise in monthly revenues with minor energy restrictions. Finally, July witnessed the most substantial improvement in profitability, with a remarkable 74.77% utilization of the installed power.

2.4 Long-term forecasting

This term of the project includes the prediction of one year to many years in the future. In 2019, research by [57] focused on predicting solar power generation using weather data and machine learning techniques. The study utilizes data gathered over three years from the Yeongam PV Power Plant in South Korea. Compared to other algorithms, the primary models performed better than the base models with the random forest regression method showing the highest performance with an R-squared value of 70.5%. In the next year, the authors in [58], driven data to model has been developed to predict the energy productivity of Australian PV plants using a hybrid deep learning methodology. The model, spanning 1990-2013, uses a retrospective dataset and outperforms other methods, with a minimal MAPE of 2.83 and a substantial R-value of 0.9. In the same year, the authors in [59] approach combines traditional time series and machine-learning forecasting methods to predict PV power generation in Korea. Three meta-learner models ARIMA, VAR, and LSTM based on CNN were used to ensemble the superior predictive capability, achieving a 30% prediction error and 59% of the MLP model's MAE, 36% root mean squared error, and 34% MSE.

Similarly, the authors in [60] compared the effectiveness of ANN and MR models in predicting PV power using data collected from a Hungary-based solar farm from April 13, 2017, to April 18, 2020, and historical weather and PV data were used to build models. The hybrid input method significantly improved the prediction accuracy of both MR and ANN techniques, achieving a COD of 0.95, MAE of 16.05, MSE of 835.68, and RMSE of 28.90. A study by [61] also compared five machine-learning models for predicting solar PV power in Saudi Arabia using meteorological parameters over the past four years. The results show that, in comparison, the suggested ENBG-FM fared better during the training and testing stages, with RMSEs of 15.91 throughout training and 19.66 W during testing. In contrast, the scholars in [62], developed a machine learning approach for long-term solar resource assessment and PV energy prediction using hourly data from the NSRDB dataset in Mexico established for its grid which obtained GHI and ambient temperature data and created energy distribution maps. The methodology identified that high radiation levels and lower temperatures resulted in higher PV energy production, confirming its reliability and effectiveness. Recently, a study by [63] presented an intelligent model for accurate prediction power generation in Saudi Arabia, using the SSA. The model predicts SPV power production using meteorological parameters in the Qassim region of Saudi Arabia over the past ten years. Model performance was evaluated through RMSE and MSE values, resulting in 1.45% and 2.12%, respectively. Finally, Table 1 summarizes the literature linked to this paper, including the location of modeling, period, and main results. The use of PV energy has significantly expanded in recent years, driven mainly by policies and goals aimed at addressing climate change; accurate production forecasting is essential for effective forecasting of PV power to minimize any adverse effects on solar resources [62].

Table 1. Summary of recent PV power forecasting studies

Study	Authors	Location	Method	length Data
[14]	Zhu et al.	North China	WD with ANN	1 minute
[33]	Bassis,	Italy	A Bayesian-Based NN	24-hour or 48-hour
[15]	Rana et al.	Australian	NN and SVR	2 years of data
[17]	Wang et al.,	China	GCC and GA	15 minutes
[64]	Panapakidis et al.	Greece	FFNN, GA	2012 to 2014
[34]	Netsanet et al.	China	ANN	Mar. to Dec. 2014
[11]	Fentis et al.	Morocco	FFNN, LSSVR	Oct. to Dec. 2014,
[35]	Liu and associates.	Ashland	NNNBP	24 hours in advance
[16]	Sivaneasan et al.	Singapore	ANN-ECF-FLP	Jan. to Mar. 2017,
[9]	Lin et al.,	Australian	HKGE	2016 to 2018
[57]	Kim et al.	South Korea	weather data and ML	Three years
[19]	Li et al.	Belgium	RNN and BPTT	from 15 to 90 minutes
[38]	VanDeventer et al.	Australia	GA-SVM	278 days
[39]	Huang & Kuo	Taiwan	CNN	24-hour ,2015
[20]	Pitalúa-Díaz et al.,	Mexico	ANFIS	Every 5 minutes
[40]	Su et al.'s	UK	NN and ML	Mar. 2017 to Feb. 2018
[21]	Chen et al.	Australia	RCC-LSTM	Five-minute
[7]	Theocharides et al.	Cyprus	ML and SPP	Day-ahead
[53]	Yang et al.	Netherlands	RBFNN- CSO	Monthly weather data
[58]	Ray et al.	Australian	LSTM and CNN	1990-2013
[12]	P. Li et al.,	Australia	WPD and LSTM	One-hour
[22]	Behera & Nayak's	India	EMD-SCA-ELM	with 15-minute
[59]	Eom et al.'s	Korea	LSTM, and CNN.	2014 to 2017
[47]	Theocharides et al.	Nicosia, Cyprus	Bayesian NN	Two years
[61]	Alaraj et al.	Saudi Arabia	ENBG-FM	Four years
[49]	Q. Zhang et al.	Jiaxing	LM-BP neural network	January to December 2019
[48]	Kaloop et al.	Italy	ANFIS-APSO	12 and 24 hours
[23]	Ziane et al.	Adrar Province	RF, PCA	2017–2018 in 15-min.
[45]	Wang, Y., et al.	China	LSTM-GPR	2016 to 2017
[24]	Ramadan et al.'s	Korea	RNN, and GRU.	Jan. 2018 and Jun. 2019
[60]	Al-Shafeey et al.	Hungary	ANN – MR	Apr. 2017, to Apr. 2020
[46]	Konstantinou et al.	Nicosia, Cyprus	DRNN	Sep. 2016 to Jan. 2019
[50]	Li et al.	China	EEMD-SSA-LSTM	April 2017
[26]	Netsanet et al.	Beijing, China	ANN-VMD-ACO	Hourly data from 2019

Table 2. Summary of recent PV power forecasting studies(Cont.)

Study	Authors	Location	Method	length Data
[65]	Adeyemi et al.	Nigeria	MLPNN	Jan. 1 to Dec. 31, 2021
[27]	Abubakar Mas'ud's	Saudi Arabia	different ML models	Hourly, from 2016 to 2019
[29]	Abdul Baseer et al	Middle East	LSTM	10 minutes to hourly
[30]	Guanoluisa et al.	Ecuador	LSTM and CNN	From 2018 to 2020
[31]	Sauter et al.	California	ML and DL algorithms	2018 to 2020,
[66]	Nahed et al.	Algeria's	CNN and LSTM	Jan. 2013 to Dec.2015
[67]	Pan et al.	China	GAN with CAE	Jan. to Dec. 2017, 5 min.
[68]	Al-Rashidi et al.	Saudi Arabia	ANN and SVR	June 2017 to August 2018.
[25]	Khortsriwong et al.	Thailand	CNN-LSTM	Three months
[37]	Alaraj et al.	Saudi Arabia	SSA	Ten years

3 PV Power Generation

Solar PV panels are a crucial component in PV systems, apparatuses that transform solar energy (sunlight) into electrical energy through the utilization of the photon-voltage effect phenomena [69]. It is comprised of miniature solar cells composed of semiconducting materials, such as silicon. as shown in Fig. 1. These cells are arranged in a grid-like pattern and enclosed within a sturdy frame, which is equipped with a protective cover to screen them from external elements. These solar cells utilize photo polarization to capture sunlight and transform it into electrical power. When light impinges upon a solar cell, it causes the displacement of electrons inside the semiconductor material, resulting in the generation of an electric current. The diversity of solar panels is contingent upon the materials employed and the production techniques utilized. The predominant varieties of solar panels are Monocrystalline Solar Panels: Constructed from a solitary crystalline silicon, these panels are distinguished by their superior efficiency and elevated price, and Polycrystalline Solar Panels: Panels are composed of many silicon crystals. While individual panels are often more efficient, these panels are more readily accessible and cost less. Forecasting the generation of power from PV systems is a challenging instillation because of its irregular and unpredictable characteristics [70]. Therefore, the production of PV energy is influenced by various factors, such as weather conditions, wind pressure, moisture, solar radiation, ambient temperature, module temperature, and dust presence. Several researches have shown that the temperature of solar panels increases as a result of the accumulation of dust on their surface. Furthermore, the elevated temperature hurts the functioning of the PV system [2]. Fluctuations in climate can alter these variables, impacting the quantity of energy generated[13]. To prevent such scenarios, it is imperative to accurately forecast the precise moment for generating PV energy.

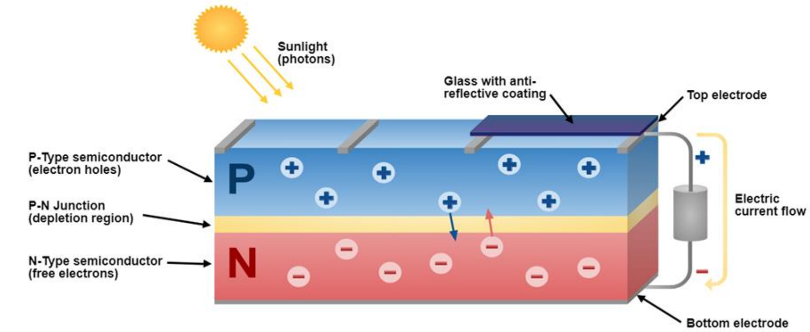


Fig. 1. The composition of PV cell

The main objective of this study is to make predictions of PV power generation to much the stability of grid-connected PV systems. The forecasting of the PV array is derived using meteorological data collected in 2021. The data tests are obtained from the website (https://climate.onebuilding.org/). The study utilized solar radiation and temperature to generate power from a PV array consisting of four units with a capacity of 1400 watts, using a MATLAB-based model. The individual specifications of the PV units are provided in Table 2. which explains the schematic diagram Fig. 2 .In the PV system model, a boost converter is implemented alongside the PV panels to increase the output voltage generated by the solar panels. Subsequently, a practical illustration of inverter regulation is conducted using a Maximum Power Point Tracking (MPPT) controller through the Perturb and Observe (P&O) technique, in combination with a DC-DC boost converter [71]. Consequently, the actual power is calculated by collecting the current and voltage, Finally, the inconsistency between the actual and prediction power is evaluated by comparing the two.

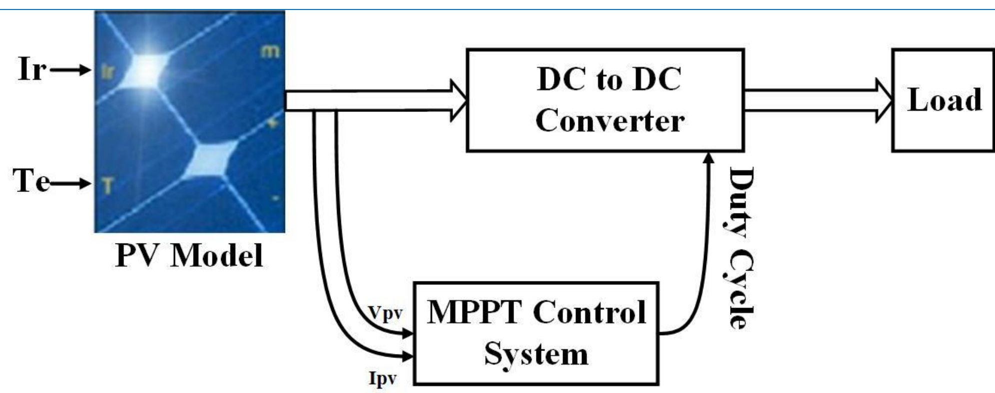


Fig. 2. Model Diagram of Photovoltaic System in MATLAB Simulink

Table 3. Specifications of the Simulink PV module test

Characteristics	Values
Cell Number	90
Open circuit voltage	41.07 V
Maximum power voltage	34.23 V
Short circuit current	11.25 A
Maximum power current	10.23 A
Maximum power point	350 W
Temperature Coefficient (Voc)	-0.272
Temperature Coefficient (Isc)	+0.061%

4 Artificial Neural Network

An ANN is a computational model that draws inspiration from the brain's mechanisms of learning and adaptation. The origin of ANN concepts may be traced back to the previous century when they were first suggested as a solution to complex issues. This period was notable for the introduction of the first McCulloch-Bates neural model in 1943 [72]. ANN has become increasingly popular in various fields. In addition, the flexibility of ANN makes it highly relevant in the field of data analysis, leading to increased interest in using it for energy prediction [73]. It is comprised of interconnected computer units called Neurons, which collaborate to analyze input and reach conclusions. The ANN model has gained the ability to extract intricate information and acquire knowledge from data with more complexity and precision, thanks to advancements in deep learning techniques [74]. The topology of the ANN model can be categorized into two types: feedforward and feedback networks. The initial category is frequently utilized since it consumes less memory during the implementation phase. Moreover, it has demonstrated significant efficacy in dealing with non-linear systems, such as a PV array [69]. To understand the process of a feedforward ANN system, the backpropagation (BP) algorithm is typically employed, comprising various layers: the input layer, hidden layers, and output layer as depicted in Fig. 3. The model is trained using the sun radiation and temperature dataset as input. An ANN with three layers was constructed. The initial and subsequent layers consist of three densely connected units with an activation function, while the third layer serves to transmit the outcomes. The rectified linear unit (ReLU) and its derivatives are commonly used in feedforward NNs, expressed as $f(x) = \max(x, 0)$ [77]. The derivative of the ReLU function at $x = 0$ is mathematically indeterminate, though it is typically assigned a value of 0 in practical scenarios. Furthermore, the neurons in each layer are interconnected via the weights (w) of the other neurons and bias (b) terms in the preceding layers, the nodes are randomly allocated weights to improve the performance of the model. The mathematical definition of this distributed processing system is given in Equation (1):

$$y_i = \sum_{i=1}^{m} w_{ij} x_i + b_i \tag{1}$$

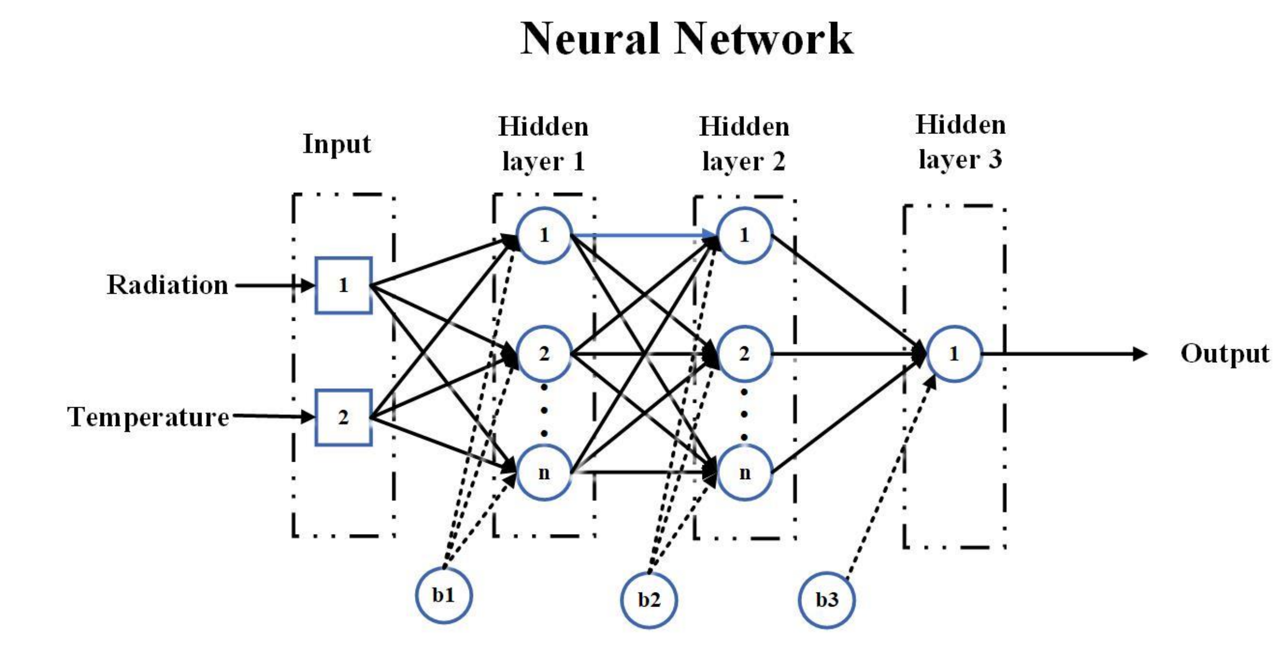


Fig. 3. Block diagram of an ANN System

5 Methodology

Selecting the appropriate evaluation criteria to analyze the effectiveness of an NN model in predicting solar power generation is a crucial aspect of any forecasting study. Various factors contribute to incorporating specific evaluation indicators to ensure the accuracy and effectiveness of the forecasting methods. Moreover, including evaluation criteria is essential for assessing the success of the NN model in predicting solar power generation. These indicators provide valuable insights into the model's accuracy, reliability, and predictive capacity, thereby enhancing the credibility and utility of the forecasting findings. This is accomplished by employing the following statistical indicators of the ANN model: (RMSE), (MSE), (MAE), and (R2) using Python language. These metrics indicate the proximity of the measured values to the anticipated PV power outputs generated by the proposed model. At the same time, the MATLAB Simulink model is designed to address the PV actual power for the same tests. Firstly, the mean square error (MSE) is defined by the following equations.

$$MSE = \frac{1}{M}\sum_{m=1}^{M}(actual - prediction)^2 \qquad (2)$$

where m ranges from 1 to M, with M being the total number of data points in the test set. Actual and predicted power values in the test set. While the root mean square error (RMSE) is defined as:

$$RMSE = \sqrt{\frac{\sum_{m=1}^{M}(actual - prediction)^2}{M}} \qquad (3)$$

MAE measures the average magnitude of errors between predicted and actual values. It provides insight into the typical deviation of the model's forecasts from the true values, allowing for a straightforward interpretation of prediction accuracy. Then, mean absolute error (MAE) is defined as

$$MAE = \frac{1}{M}\sum_{m=1}^{M}(actul - prediction) \quad (4)$$

The closer the MAE and RMSE values are to zero, the better the prediction performance. The coefficient of determination (R^2) quantifies the extent to which a statistical model accurately forecasts an outcome. The minimum achievable value for R^2 is 0, while the maximum attainable value is 1. Succinctly stated, the closer its R^2 will be to 1, the better a model is at making predictions, as shown in Equation (5):

$$R^2 = 1 - \sqrt{\frac{\sum_{m=1}^{M}(actual-prediction)^2}{\sum_{m=1}^{M}\left(actual-mean(actual)\right)^2}} \quad (5)$$

Fig. 4 illustrates the operational flow of the suggested methodology for conducting medium-term prediction of PV output power using ANN technology. Includes PV power output and weather parameter datasets like temperature, and solar radiation from January 1 to December 31, 2021, were collected from the database available on the website (https://climate.onebuilding.org/). Data collection included 8,761 samples collected every hour during the entire year of 2021. In addition, only daytime data is taken into account, while night time data is excluded, and solar radiation levels less than 15 watts/m2 are also disregarded.

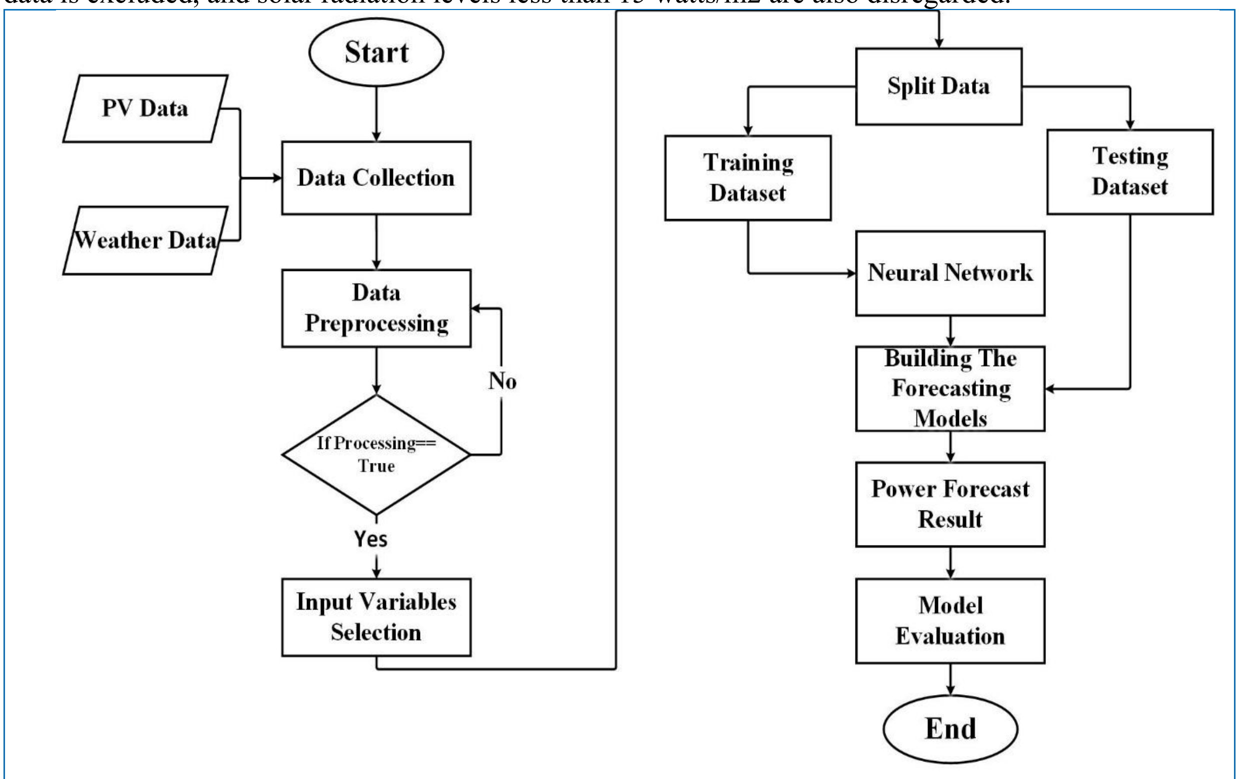


Fig. 4. The framework for the suggested approach of predicting PV power accurately using Python language.

Efficient data preparation is essential for developing accurate predictive models due of historical data may include incorrect information, which harms the model's effectiveness. That is because it is done data cleaning removing missing data, and if any errors are identified, the process is repeated to ensure data accuracy. Finally, the combined dataset was divided into two subsets. The first subset contains the training data 60% of the total data is allocated used to train the model. An additional 40% of the total data is allocated to testing the final result of this dataset. The raw dataset is segmented to obtain an accurate classifier evaluation without incurring any risks.

6 Results and Discussion

This study aims to predict the generation of photovoltaic energy using the weather data that have been collected for the period from January 1 to December 31, 2021. The outcomes of PV power production in Iraq fluctuate based on the season and regional climatic fluctuations. So, the study examined data from four months, where one month of each season was chosen to forecast photovoltaic power generation where January represents winter, March represents spring, July represents summer and September represents autumn. The first step was data division for each month into training and testing sets. In the second step, the data was trained using a neural network where the weights were randomly assigned using Python libraries such as TensorFlow and Matplotlib. Finally, the prediction models are compared to actual PV power outputs, calculated using MATLAB Simulink, shown in Fig 2, and optimized error parameters. The following are the outcomes for those particular months:

6.1 January Forecasting Term

In January, 310 sample data tests were gathered to design the prediction model of PV grid-connected system. The data were divided into two sets: the training data, which ranged from 8:00 am on January 1st, 2021, to 11:00:00 am on January 19th, and the test data, which encompassed the period from 12:00:00 pm on January 19th to 5:00:00 pm on January 31st. Table 3 displays the MAE, RMSE, and MSE values, which are approximately 123.1176 W, 154.8474 W, and 23977.7275 W, respectively. A decrease in these evaluation metrics indicates a higher level of accuracy in the prediction. Fig. 6 (a, b, d) illustrates that the values decrease as the number of epochs increases during the training the neural network. Furthermore, there was a reduction of 3.96% from the March and 2.07% from the July in the R2 value, resulting in an overall decrease of 11.61% from September. The correlation coefficient for the proposed model was reported as 0.8146, indicating that higher R2 values correspond to greater prediction accuracy. Hence, the comparison results between expected and actual capacity are showed upward and downward trends due to heavy clouds and rainfall in this month usually as shown in Fig 6(e). In addition, the energy production was witnessed a decline between 8:00 am to 5:00 pm on January 22, as shown in Fig 5, where power production is expected to reach approximately 390 watts. This can be attributed to decreased solar radiation caused by dense cloud cover. Furthermore, at times, expected energy generation in Iraq during January can be lower than actual energy due to limited daylight hours and weak solar radiation. Nevertheless, PV energy still contributes to electricity generation.

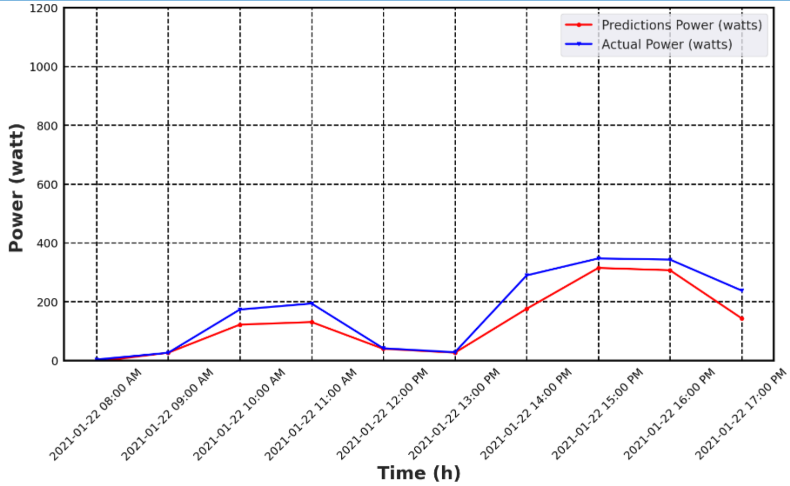
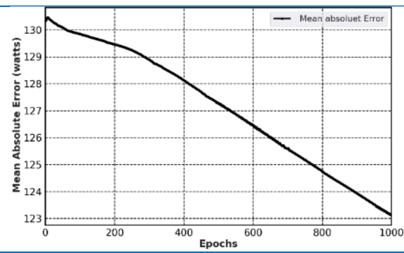
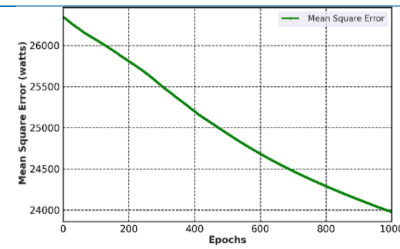


Fig. 5. Relationship Between Actual and Predicted Power from 8 AM to 5 PM on the 22th, in January.



(a)



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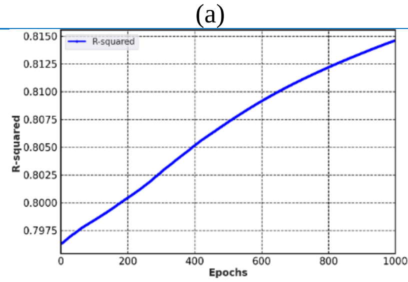

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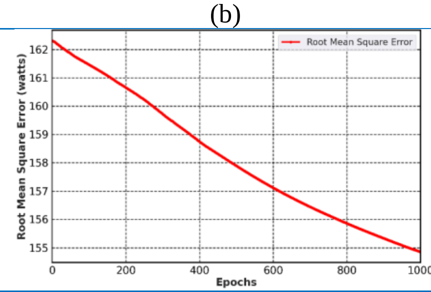

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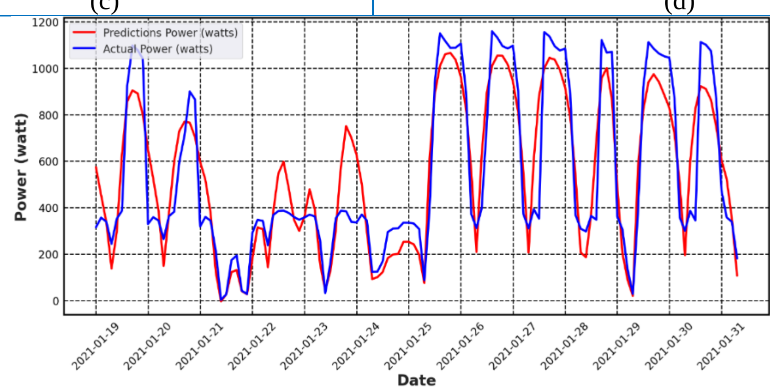


(e)

Fig. 6. The results of January of (a) MAE, (b) MSE, (c)R2, (d) RMSE, and (e) the relationship between actual power and prediction power from 8 am to 5 pm

6.2 March Forecasting Term

In March, a grand number of 371 samples were collected. Those data were partitioned into two distinct sets: the training data, encompassing the time interval from 03/01 07:00:00 to 03/19 10:00:00, and the test data, spanning the period from 03/19 11:00:00 to 03/31 18:00:00. Consequently, Table 3 displays the MAE, MSE, and RMSE values, which are approximately 97.2655 W, 20500.9691, and 143.1816 W, respectively. A decrease in these evaluation metrics indicates a higher level of precision in the prediction process. The trend illustrated in Fig. 7 shows a consistent decline in values as the number of epochs used for training the NN increases. Moreover, there was a notable increase of 3.96% and 1.93% in R2 values from January and July, respectively. The correlation coefficient presented in Table 3, with a value of 0.8482, signifies a direct relationship between the R2 metric and the accuracy of predictions. This is because of the increased number of samples that can be attributed to longer daylight duration and abundant solar radiation, which positively impact the performance and outputs of PV systems. Fig. 8 (e) shows an upward trend in energy generation from 7:00 AM to 12:00 PM, followed by a gradual decline. During the period from 7:00 AM on the 27th to 5:00 PM on the 28th, a decrease in power generation occurred. During this period, solar radiation ranged from 7.8 to 190 watts per kilometer due to the presence of dense clouds and rainfall, as shown in Fig 7. However, the relationship between expected and actual power showed improvement compared to January.

6.3 July Forecasting Term

A large number of samples, totaling 435, were collected in July and are divided into two groups: the first group is collected 07/01 05:00:00 to 07/19 11:00:00, while the second group is covered 19/07 12:00:00 to 31/07 19:00:00. Table 3 and Fig. 8 (a,b,d) displays the MAE, MSE, and RMSE values, which are around 87.9430 W, 14624.2784 W, and 120.9309 W, respectively. Consequently, a decrease in the given evaluation measures indicates an increase in the accuracy of the prediction. The data also revealed that the MAE and RMSE values were significantly lower compared to those reported in January, with a decrease of 28.57% and 21.9%, respectively. Furthermore, the R2 value for the proposed model is documented as 0.8318, indicating that a higher R2 corresponds to a greater level of prediction accuracy. Although the number of samples exceeded the other months, the energy production was not superior compared to September. This can be attributed to the high temperatures experienced in Iraq during July, which negatively affected production. However, Fig. 9 (e) demonstrates that most of the time a symmetrical relationship between the actual and predicted power, making it an ideal time for generating electricity using PV systems.

6.4 Setember Forecasting Term

In September, also a large amount of data was collected reaching a total of 390 samples that were divided into two groups: preparatory data, which spanned from the first day of September at 06:00:00 to the eighteenth day of September at 16:00:00, and evaluative data, which covered the period from the eighteenth day of September at 17:00:00 to the thirtieth day of September at 18:00:00. The optimal MAE, MSE, and RMSE values obtained are approximately 92.2990 W, 8892.3090 W, and 72.4880 W, respectively, as indicated in Table 3. The data also revealed that the MAE and RMSE values were significantly lower than those reported in January, with a decrease of 41.12 W and 39.1 W, respectively. Furthermore, the suggested model exhibits an exceptional R2 value of 0.9216, surpassing other results. This can be attributed to favourable weather conditions, characterized by clear skies and ample sunlight. Ultimately, in Fig. 10 (e), the relationship between expected and actual energy is shown, indicating a convergence between the expected value and the actual value as a result of the large amount of sunlight as well as moderate temperatures.

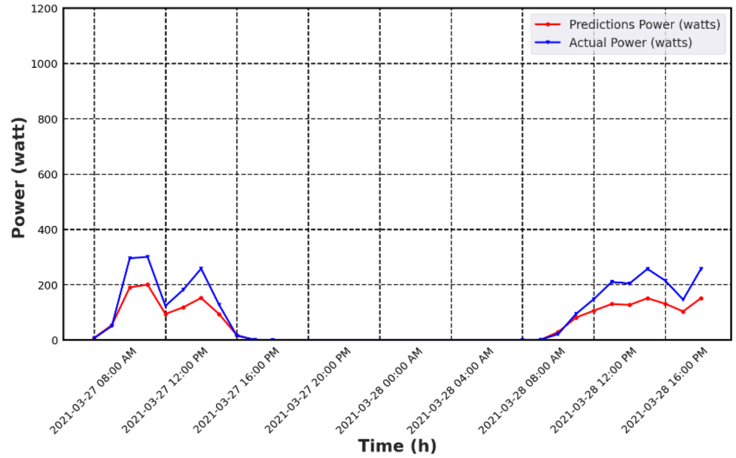
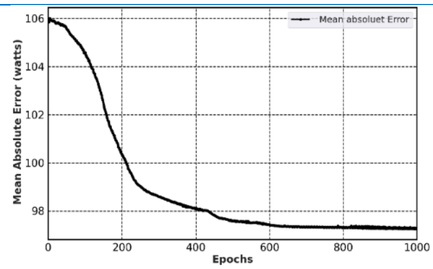
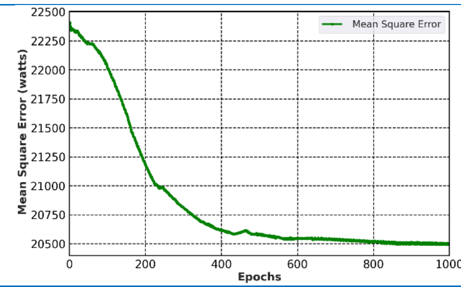


Fig. 7. Relationship between actual and prediction power from 7am to 5pm on the 27th and 28th in March.



(a)



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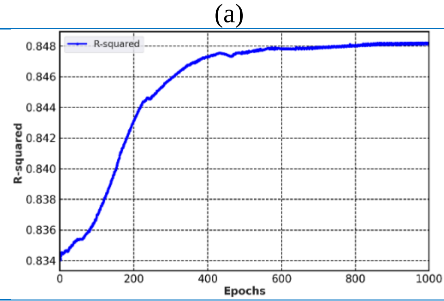

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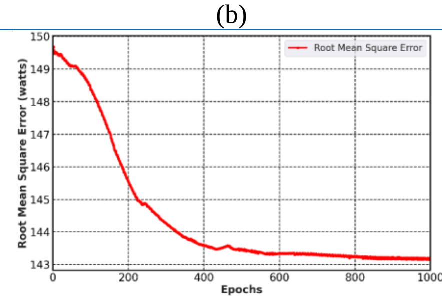

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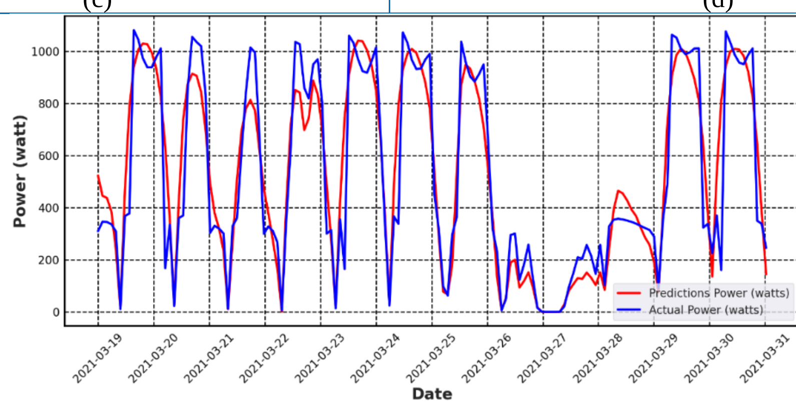

(e)

Fig. 8. The results of March of (a) MAE, (b) MSE, (c)R2, (d) RMSE, and (e) the relationship between actual power and prediction power

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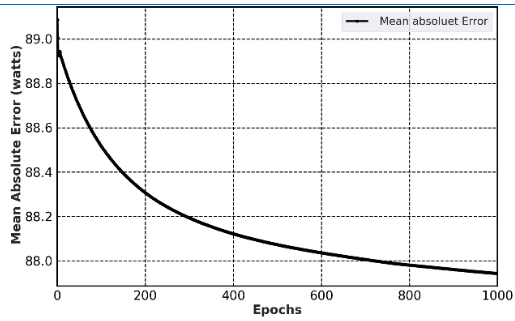
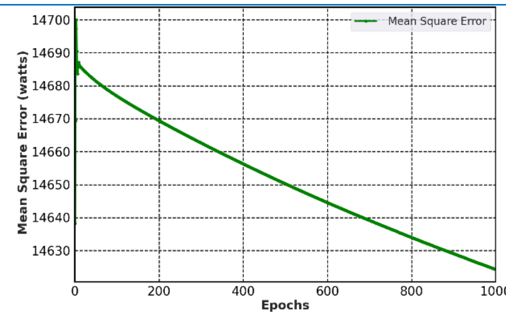


(a)



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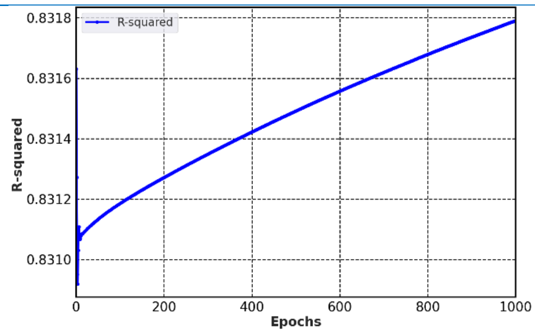

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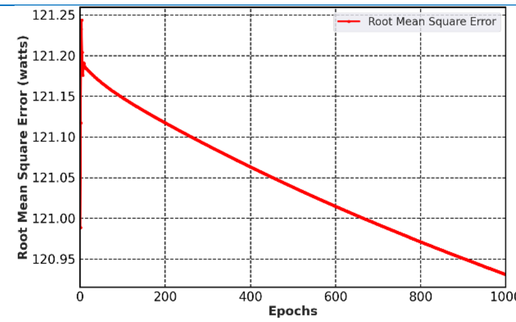

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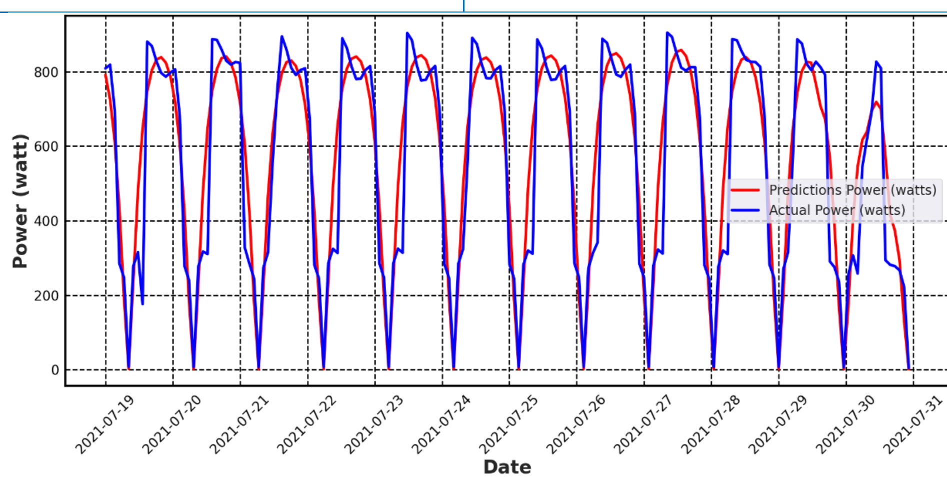

(e)

Fig. 9. The results of July of (a) MAE, (b) MSE, (c)R2, (d) RMSE, and (e) the relationship between actual power and prediction power

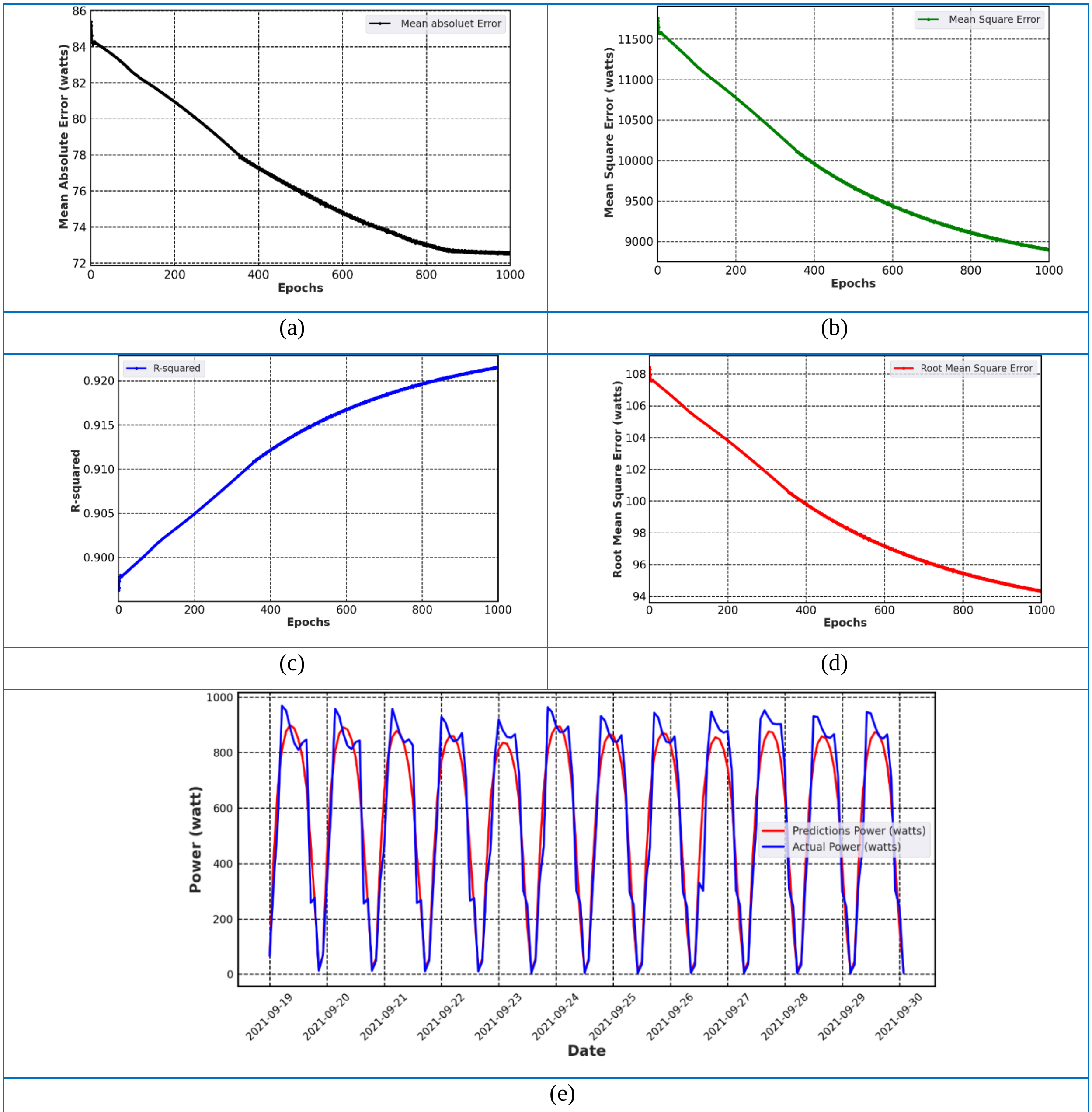

Fig. 10. The results of September of (a) MAE, (b) MSE, (c)R2, (d) RMSE, and (e) the relationship between actual power and prediction power.

Lastly, the findings Fig; 6,8,9, and 10 demonstrate that September has exhibited the most favorable values based on the established criteria, therefore it is considered the month with the highest expectations for the generation of PV energy. Owing to its abundant solar radiation resulting from the lack of cloud cover and moderate temperatures. Conversely, January witnessed a relative decline in solar energy generation due to the limited daylight hours and the presence of unpredictable weather patterns characterized by weak sunlight, frequent rainfall, and overcast skies. Consequently, it is regarded as the least preferable among the months for making predictions. Nevertheless, the currently available solar energy still plays a role in power generation. On the other hand, June is characterized by high temperatures and ample sunlight, making it a favorable period for solar system electricity generation. Thus, its performance has surpassed that of March in terms of RMSE and MAE. In March, the R-Square value had a marginal rise of 0.0161 compared to July and 0.037 compared to January. This can be attributed to the fact that during this period, the duration of daylight hours increases, leading to an abundance of solar radiation. Additionally, the temperatures during this time are moderate, further enhancing the efficiency of solar energy systems. Finally, the proposed forecast results for PV in June, March, July, and September are explained in Table 3.

While the NN demonstrated good performance, it did not reach the desired level compared to other methods mentioned in the study. This is because some of these methods have been refined and integrated with other technologies, resulting in enhanced forecasting capabilities. Additionally, the results indicated that the models proposed in the previous research outperformed NN in certain cases, particularly concerning accuracy and error measurements such as RMSE and MAE. This suggests that the improved and combined methods were superior in predicting photovoltaic power generation under the given conditions.

Table 4. Summarized forecasting results for PV prediction model.

Month	RMSE (watts)	MSE (watts)	R2	MAE (watts)	Sample	Test
January 1	154.8474	23977.7275	0.8146	123.1176	310	124
March 3	143.1816	20500.9691	0.8482	97.2655	371	149
July 7	120.9309	14624.2784	0.8318	87.9430	435	174
September 9	94.2990	8892.3090	0.9216	72.4880	390	156

7. Conclusions

This study has been provided a comprehensive assessment of prior studies between 2015 to 2023 that been examined the prediction of PV power generation for various forecasting times. As well as it has been discussed the neural network's performance in dealing with PV power prediction challenges for the collected data of weather conditions in southern Iraq. To sum up, the data were partitioned into a training set comprising 60% of the total data and a testing set comprising 40% of the total data. Then, Network performance based on Python Language has been assessed using various statistical metrics for different weather cases. Finally, the PV actual power has been determined based on the same weather conditions using MATLAB Simulink. The findings demonstrate the efficacy of the NN performance over the specified four-month period, as it appears that September has the most favorable values, with MAE of 72.488 W, RMSE of 94.299 W, and R2 of 0.9216. Consequently, it is the month with the highest expectations for PV generation due to the abundance of solar radiation from the lack of cloud cover and moderate temperatures. In contrast, January saw relatively low solar power generations due to limited daylight hours and unpredictable weather patterns characterized by weak sunlight, frequent rainfall, and overcast skies, with the value of an MAE of 123.1176 W, an RMSE of 154.8474 W, and an R2 of 0.8146. In future work, actual PV generation based on an optimization algorithm will be used to design an accurate prediction model of the PV system.

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Conflicts of Interest: The authors declare no conflict of interest.

List of abbreviations of this work

Full From	Abbreviation	Full From	Abbreviation
Photovoltaic	PV	Conventional Neural Network	CNN
Machine Learning	ML	Least Square Support Vector Regression	LSSVR
Statistical post-processing	SPP	Mean Square Error	MSE
A Genetic Algorithm	GA	Coefficient of Determination	R2
Linear Discriminant Analysis	LDA	Mean Absolute Error	MAE
Elman Neural Network	ENN	Mean Absolute Relative Normalized Error	MARNE
Long Short-Term Memory	LSTM	Radial Basis Function Neural Network	RBFNN
Wavelet Decomposition	WD	Back-Propagation Through Time	BPTT
Artificial Neural Networks	ANN	Radiation Classification Coordinate	RCC
Fast Deep Feedforward Network	FAST-DNN	Sine Cosine Algorithm	SCA
Support Vector Regression	SVR	Random Forest	RF
Social Swarm Optimization	SSO	Principal Component Analysis	PCA
Cuckoo Search Optimization	CSO	Recurrent Neural Network	RNN
Sparrow Search Algorithm	SSA	Gated Recurrent Unit	GRU
Empirical Modal Decomposition	EMD	Mean Bias Difference	MBD
Virtual Mode Decomposition	VMD	Mean Absolute Percentage Error	MAPE
Ant Colony Optimization	ACO	Grey-box model	GB
Adaptive Neuro-Fuzzy Inference System	ANFLS	k-Nearest Neighbours	KNN
Extreme Learning Machine	ELM	Quantile random forest	QRF
Multilayer Perceptron Neural Network	MLPNN	Ensemble of methods	ENS
Generative Adversarial Network	GAN	Generalized Regression Neural Network	GRNN
Convolutional Autoencoder	CAE	Multiple Regression	MR
Wavelet Packet Decomposition	WPD	Recurrent Neural Network	RNN
Salp Swarm Algorithm	SSA	Root Mean Square Error	RMSE
Gray Correlation Coefficient	GCC	Dynamic Recurrent Neural Network	DRNN
Feed-Forward Neural Network	FFNN	Numerical Weather Prediction	NWP

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