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An Efficient Neural Network Model for Solar Energy Prediction

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ABSTRACT

Solar energy is the ultimate source to fulfill the increasing demand of energy. It is the renewable energy source that improves the reliability and effectiveness in electricity consumption and utilization. This increasing demand also causes the heavy load and unequal distribution of energy. Solar power prediction is one of the effective technique that can identify the available and generated solar power in real environment. Accurate prediction of solar power results in equalized and balanced distribution of electricity. In this paper, an advanced deep learning based neural network model is proposed for effective and accurate prediction of solar energy. In the proposed model, deeper analysis is performed to determine the relationship of solar energy generation with 11 different atmospheric features. The novelty of this model lies in meticulously selecting and utilizing these features for designing the highly accurate prediction model. Accuracy of the proposed model is compared against existing persistent MLP model with the aid of RMSE, MSE, MAE and R^2. The results show that RMSE, MSE and MAE values obtained for proposed model are 1.37, 1.88 and 0.728 Wh/m^2 respectively. Whereas the error values obtained from persistent MLP method are 2.604, 6.781 and 1.127 Wh/m^2 respectively. A significant improvement of 7.5% in R^2 value confirms the excellent performance of the proposed neural network model in predicting solar generation.

Keywords: *Multi-layer perceptron, Neural Network, Deep learning, Solar Energy prediction.*

1. INTRODUCTION

Electrical power is one of basic need that is required for survival, business and comfort. With the advancement of Internet of Things (IoT) and other smart technology, life is very much dependent on technology. The electric power is required to keep running and functioning these application, devices and environment. These devices and environment has increased the demand of electric power as well as the seamless power supply. This demand is increased at industry and residential level. This increased demand also identified the problem of demand and supply balance. Even the available traditional sources of electricity are not capable to fulfill this demand. This problem got the attention of renewable sources of power such as wind, solar etc. The other problem of conventional energy sources was its impact on atmosphere. In recent years, pollution and other unfavorable changes are noticed in the environment. These changes also identified that the fuel based plants should be replaced by renewable energy sources [1]. It is found that the clean energy is an effective substitution to the conventional energy sources. Solar energy is one of the most promising sources of clean energy that resolves challenges of conventional energy. The solar power generation and prediction is affected by various factors including cloudy weather, wind, humidity and other atmospheric conditions. The prior forecasting of solar power improves and equalize the distribution of energy to fulfill demand of customers [2].

Fluctuations, randomness and intermittency are the key limitations of solar energy. Accurate prediction of solar energy output is a critical challenge. A dynamic model is required to analyze the current and energy of solar system that is integrated with power grid [3]. Various parametric, statistical and machine learning methods were investigated by the researchers for effective, accurate and optimized prediction of solar power prediction. The historical data, daily energy consumption data, atmospheric conditions are the different kinds of features that are processed by machine learning algorithms for solar power prediction. In improved form, ensemble learning model and optimized learning models are also used for predicting solar power. In an improved model, the attributes used in the prediction system are also analyzed respective to its significance. Feature weight and feature selection methods are used for identifying and filtering the valuable features. The ranking and feature dependency methods can be applied to measure the quality of available features and to prioritize them based on their significance, application dependency and relevancy [4, 5, and 6].

In this paper, a deep learning inspired model is applied on solar panel and atmospheric features for accurate forecasting of solar energy generation. The model is configured by setting up the weighted parameters based on the input data. In this section, significance, features and application of solar power prediction and machine learning algorithms are provided. In section 2, work provided by earlier researchers are discussed in detail. In section 3, the proposed deep learning based model is described with associated features and configuration. The significance and functionality of the model is defined here. The details of the dataset and analysis parameters utilized in this paper are also provided. Section 4 compares the prediction results of the proposed model with the baseline model (MLP) to examine the accuracy of proposed model. In section 5, conclusion of the work is provided.

2. LITERATURE REVIEW

Mohammed et al. proposed ensemble learning based probabilistic approach for solar power prediction [7]. The proposed ensemble learning method was defined with multiple machine learning algorithms with initial settings. Normal distribution was used within the algorithm for optimizing the forecast. The base models used in this research were decision tree, random forest and KNN regression models. The model achieved effective outcome with average 0.0148 pinball losses. In [8], authors proposed an adaptive curve fitting based mathematical model for solar power forecasting. They used the real-time power, clear sky reference power and weather information for optimizing the solar power prediction or forecasting. They analyzed the effect of atmospheric features on solar power outcome. These parameters were eliminated from the system for observing the direct sensing of solar output and forecasting methodology. They utilized a time segmentation based method for identifying the difference between reference and actual power. In [9], authors proposed an active demand side analysis based recurrent neural network model for effective solar forecasting. They collected the solar data under effect of humidity, wind speed, temperature, and cloudiness. The proposed model achieved accurate results in normal and sunny conditions. The prediction in cloudy days was lesser accurate.

In [10], authors proposed an artificial neural network (ANN) based model to predict the power generated by multi crystals solar photovoltaic modules. They defined the work under two ANN models called multi-layer perceptron and radial basic function. The proposed model achieved effective correlation and up to 0.96 of R^2 value. Authors in [11] proposed a hybrid model by combining the back propagation neural network (BPNN) and genetic algorithm for predicting the energy production from photovoltaic system. The historic output data, metrology data of delivery day and historical metrology data were considered as input parameters. A mapping function was defined to identify the relation between input and output data. The proposed optimized BPNN with initial thresholds and weights was performed for accurate prediction of output power. The analysis results identified significant improvement in speed and accuracy against existing power prediction models. Authors of [12] proposed SVM based short-power predictor by processing the multi-source fused data. The power, satellite and weather features were utilized in this model for improving the accuracy rate. The structured and sequence features were acquired and processed by extended machine learning algorithms for generating the non-linear dependencies and to improve the prediction results.

In [13], authors proposed the probabilistic hidden Markov model for time-series energy prediction for smart solar system. The model was designed with two integrated phases called panel level monitoring and solar power prediction. The system was analyzed under real-time constraints including weather conditions. The significance of different parameters and its effect on panel state was observed using these parameters. The correlation based predictor was also integrated within the system that mapped with HMM and achieved the effective accuracy. In [14], a novel methodology called Mycielski-Markov for optimizing the performance of short-term based solar power prediction was proposed. The proposed probabilistic method applied the Markov chain method on historical data and solar radiation data for predicting the solar power in deterministic way. The proposed model achieved 87% accuracy with effective correlation of determination values.

Authors of [15] improved the solar power forecasting based on daily collected metrological information. The active and market power generation based model was proposed for effective reserve allocation. The statistical significance based metrological parameters were analyzed using regression modeling for improving the prediction results of solar system. In [16], a mathematical model to handle the uncertainties of solar system and to forecast solar energy accurately, was proposed. The model used the plant specification and weather information to predict the solar outcome for the next seven days. The effect of solar irradiance, panel efficiency and ambient temperature were also analyzed in the proposed model. In [17], feed-forward neural networks based irradiance prediction model was proposed. This work utilized the satellite and historical irradiance images as input. The extracted features were processed by PCA to identify the significant features. This PCA-FNN based model achieved the effective accuracy for long-short term prediction. The proposed model achieved the effective outcome in terms of power utilization and reduced the energy loss and operating cost. Sun et al. applied the specialized Convolutional neural network (CNN) model to predict the short term solar outcome by utilizing the sky images and solar panel history [18]. The proposed model achieved 26.2% forecast on sunny and 16.1% on forecast skill. Naing et al. combined the mathematical computation with neural network for forecasting of solar radiation [19]. The geographical and metrological information was used in this research. The model achieved effective results with lesser mean bias error, root mean square error and mean absolute percentage error.

After carefully analyzing above mentioned research studies it was observed that most of the studies developed prediction model for solar irradiance. Solar energy/power output is then estimated based upon the predicted solar irradiance values. Only few studies predicted solar power/energy directly using weather parameters such as solar radiation/irradiance (W/m^2), temperature, humidity, and wind speed as input features. Therefore, in this paper some other important features such as Heat Index, Humidity Index, pressure and high solar radiation are explored to efficiently increase the prediction accuracy of proposed model.

3. MATERIAL AND METHODS

Since solar power generation is dependent on atmospheric parameters including temperature, humidity, wind speed etc. These parameters not only affect the amount of generated energy but can affect the performance of prediction system also. In this section, the detailed model, its features and functionality are described. The basic concepts of machine learning and multi-layer perceptron (MLP) are also discussed in this section. The features and parameters of the proposed model are defined to explore the significance and behavior of the model. The experimental environment and associated data is also described in this section. Based on this dataset, the functional implementation of the proposed model is performed.

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This section involves the accuracy measures used to test the performance of both the models.

3.1 Data description

For experimenting and validating the proposed model solar energy data is collected from secondary sources. This data is taken from a project of UK Power Networks. Its basic attributes, relevancy and characteristics are described in Table 1. The table contains the physical and experimental characteristics. The dataset has 60,035 total observations which are sampled at interval of 30 minutes. It is divided into training set and testing set in ratio 1/3.

Table 1. Details of the selected dataset.

Properties	Values
Source Project	UK Power Networks
Physical Characteristics	Domestic Site with Solar Panels, 20 Substations, 10 Domestic Premises
Time Interval	30 Minutes
Total Observations	60035
Training Set Size	40023
Testing Set Size	20012

3.2 Persistent MLP Model

Multilayer perceptron (MLP) is an extension of feed forward neural network [20, 21]. This model is defined as a regression model with three connected layers as shown in Fig. 1. The input layer represents the features as input. In this work, the solar panel features and environmental features are collectively used as the feature set. This feature set is passed as input on input layer of this model. The output layer produces the final prediction or forecasting result. There lies 'n' numbers of hidden layers between input and output layer. These layers are the actual computational engine of MLP. In MLP, the data flows from input to output layer in a forward direction. In this model, the neurons are trained using back propagation learning technique.

In this paper, the persistent MLP model is applied on the common features taken from dataset and as observed in the literature. The most used features are humidity, temperature, wind speed and solar radiation/irradiance (W/m^2). So, based on this six input features viz. Outdoor temperature, indoor temperature, low temperature, high temperature, solar irradiance (W/m^2) and wind speed (m/s) are selected for prediction of solar energy using MLP. Fig. 2 is showing the relationship derived between solar energy and considered parameters.

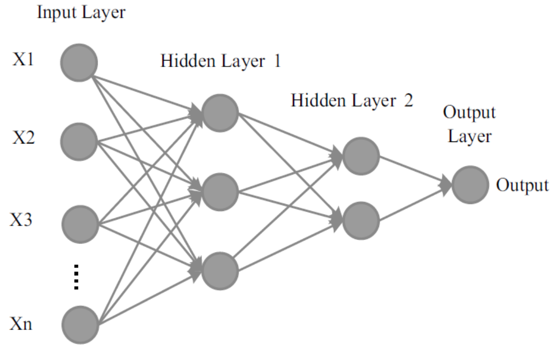

Fig. 1. Multilayer Perceptron Architecture.

This figure shows that the maximum solar energy is obained for 10 to 15℃ outdoor, high and low temperature features. For indoor temperature, the maximum solar energy is achieved for 25 to 30℃. In case of solar radiation, the maximum solar energy is obtained for values between 800 and 1000 W/m^2. The effective solar energy is obtained with least wind speed upto 5 m/sec. After finalizing the input parameters, the MLP network is configured with two hidden layers. The first layer contains 12 neurons and second layer has 8 neurons. The output layer is defined with single neuron. The activation and optimizer functions used in this model are 'rectifier' and 'adam'. The experimentation is conducted for 200 iterations. Mean squared error (MSE) is the loss function used in this model for analyzing the performance of the system. The experimentation results are conducted on error rate and mapping of prediction and true values.

Fig. 3 shows the mapping of predicted and true solar energy output values obtained for 100 randomly selected observations from testing set. It clearly shows that the MLP predicted values are not completely overlapping the true values and there still lies some scope for improvement. The error based analysis is provided in Fig. 4. Fig. 4 shows the MSE based error analysis for training and testing sets using MLP prediction model. The line graph shows that the error rate of training set is significantly lesser than testing set. Here, effective results are obtained using MLP model but loss function reflects significant gap between training and testing set errors throughout the iterations. Also, MSE value has not reduced by significant amount over the process. Therefore, a deep learning based neural network model is proposed in this paper for improving the accuracy of solar energy prediction.

3.3 Proposed deep learning based neural network model.

Deep Learning is an extensive form of machine learning and neural network methods that can be applied to perform prediction and classification in various domains [22, 23, and 24]. In this research, deep learning model is applied on solar data for effective prediction of solar power generation. Deep learning is an effective, characterized and extensive form of neural network. The solar power prediction is one of challenging problem for which data is collected over a larger time span.

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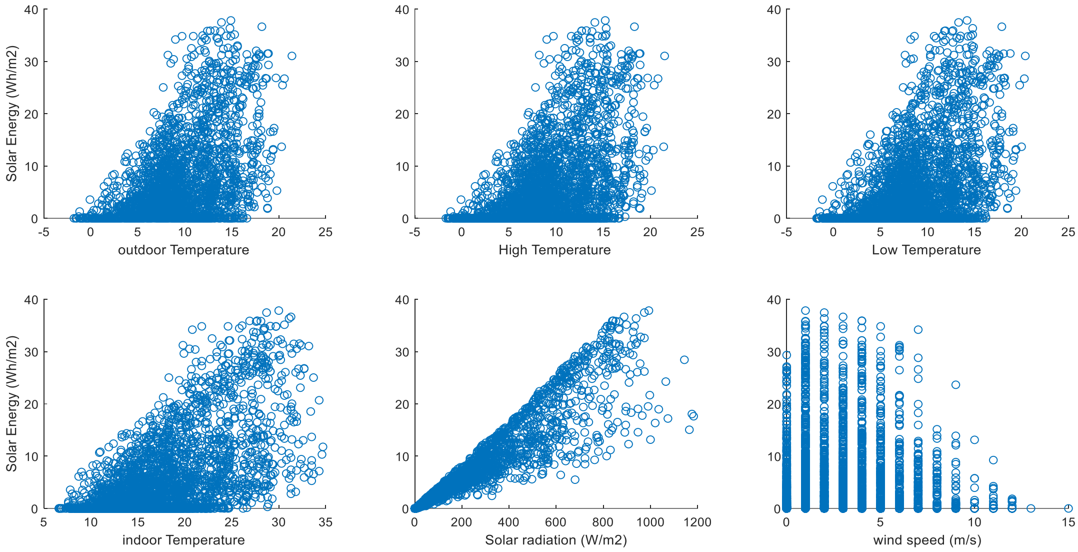

Fig. 2. Characteristics of solar energy and selected input features.

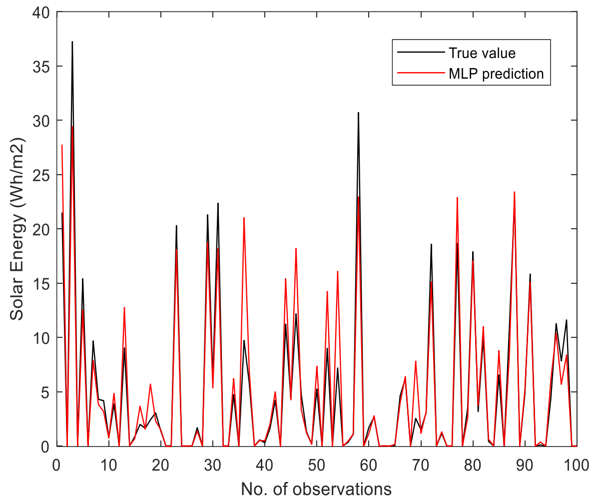

Fig. 3. Prediction results of MLP model.

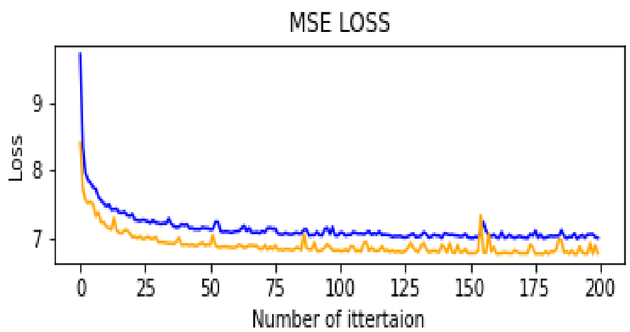

Fig. 4. Loss function of MLP model.

This data is collected on hourly basis, daily basis or monthly basis. As we discussed earlier, the functional behaviour of solar power generation is also affected by various atmospheric factors including rainfall, temperature, humidity and windspeed. The deep learning provides the effective models and parameters for extracting the most relevant features and information from the available dataset. In a deep learning model, the numbers of hidden layers are defined to perform control and extraction of features. The model can be applied on larger dataset to learn the features and to predict the solar power [25, 26, and 27].

In this paper, a deep learning based neural network model is proposed for improving the effectiveness of solar energy prediction. Before applying the deep learning model, input features are analyzed to identify the most effective properties that can produce accurate outcome. In this model some new features are considered that can provide effective and accurate prediction. For successful implementation of proposed model, 11 features are selected related to solar energy system. These features are Outdoor temperature, Indoor temperature, High temperature, Low temperature, solar irradiance (W/m^2), Wind speed (m/s), High solar radiation, Pressure, Humidity, Heat Index, and THW (Temperature Humidity Wind) Index. For validating the significance of these features, effect of individual feature is analyzed respective to generated solar energy. This relationship among features and solar output is shown in Fig. 5.

Fig. 5 shows the evaluation of significance of each parameter seperately respective to solar energy. This figure shows that high solar power is obtained for 12 to 17°C outdoor, high and low temperature. In case of indoor temperature, maximum solar energy is obtained for values of 25 to 30°C. The pressure effect is higher for values 757 to 767. The solar output gives better result with lesser humidity (40 to 60) values, and wind speed (<5m/sec). The higher solar readitions and total

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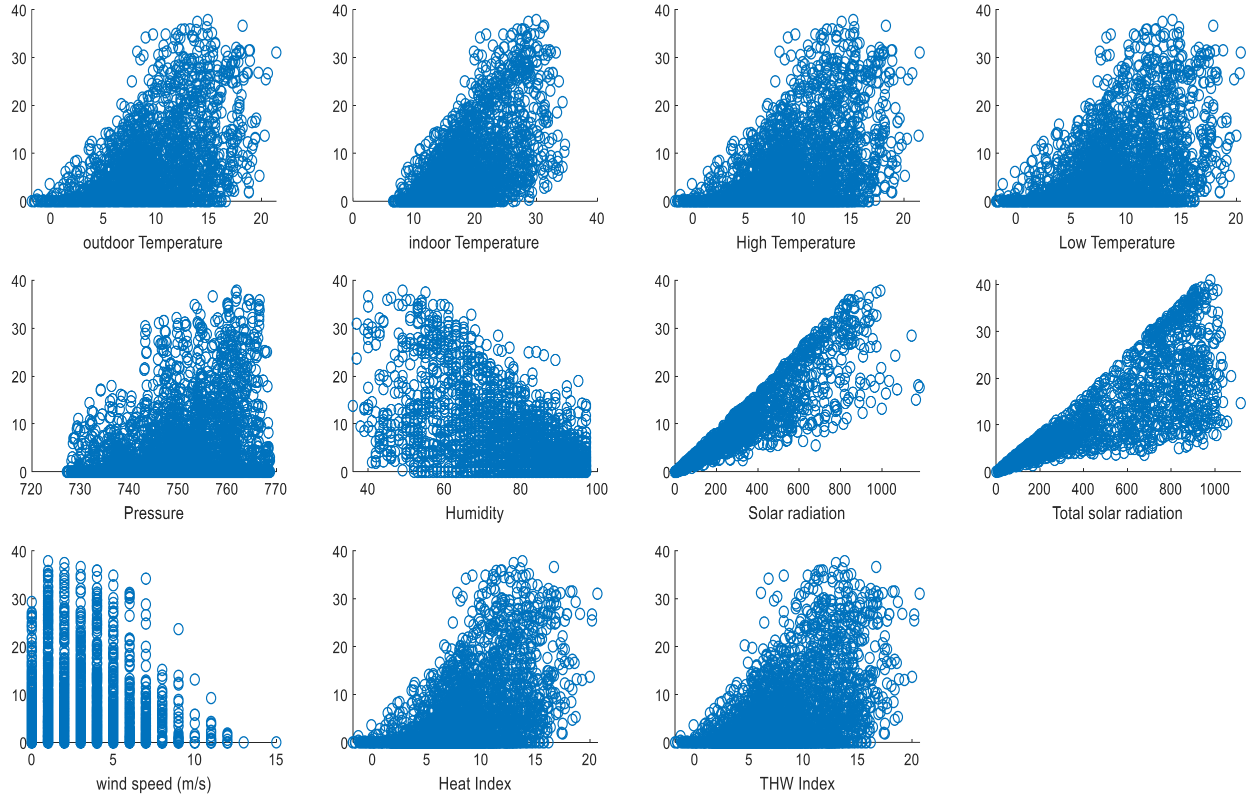

Fig. 5. Characteristics of selected 11 features with solar energy generation.

solar radiations of 800 to 850 W/m^2 shows the higher generation of solar energy. The heat index and THW index between 8 to 13 provides the maximum power from solar energy. After validaing the parameteric significance, deep learning based neural network is configured and applied on these parameters. Fig. 6 is showing the experimented deep learning model. This model is defined with five layers. It is composed of four hidden layers. The number of neurons in first layer are 32, in second hidden layer 16, in third layer 12 and in fourth layer 8 neurons are used. The output layer is defined with single neuron. ‘rectifier’and ‘adam’ are the activation and optimizer functions used for developing this model. The model is trained for 100 iterations and accuracy analysis is done using MSE loss function.

In this proposed work, the deep learning model is used in extensive form by using a batch normalization technique within the model. This technique improves the training time of multi-layered deep learning neural network. This approach can regularize the system and improve the accuracy producing least possible error. The experimental proof of performance is provided in section 4.

After designing the model defined in Fig. 6 with defined configuraiton and input features, the experiment is conducted to verify the accuracy and error rate of this model against true values and persistant MLP model. Fig. 7 shows the solar energy predictions with its true values. Nine sets of 100 observations are selected randomly from the testing set in order to examine the extent of accuracy obtained in prediction results by the proposed model. It is clearly visible from Fig. 7 that the predicted values almost overlap the true values. It shows that the proposed model achieved the accurate and significant results.

The error based analysis is also conducted for analyzing the reliability and performance of the proposed model. MSE is the error function used to analyze the loss of the proposed model as shown in Fig. 8. The loss function attains value close to zero after 40 iterations itself for both training and testing datasets. The proposed model certainly shows higher prediction results. These results show that the proposed model is versatile and highly accurate.

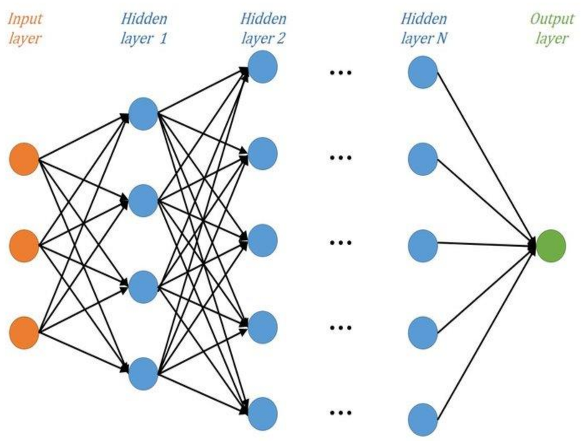

Fig. 6. Structure of Deep Learning inspired neural network.

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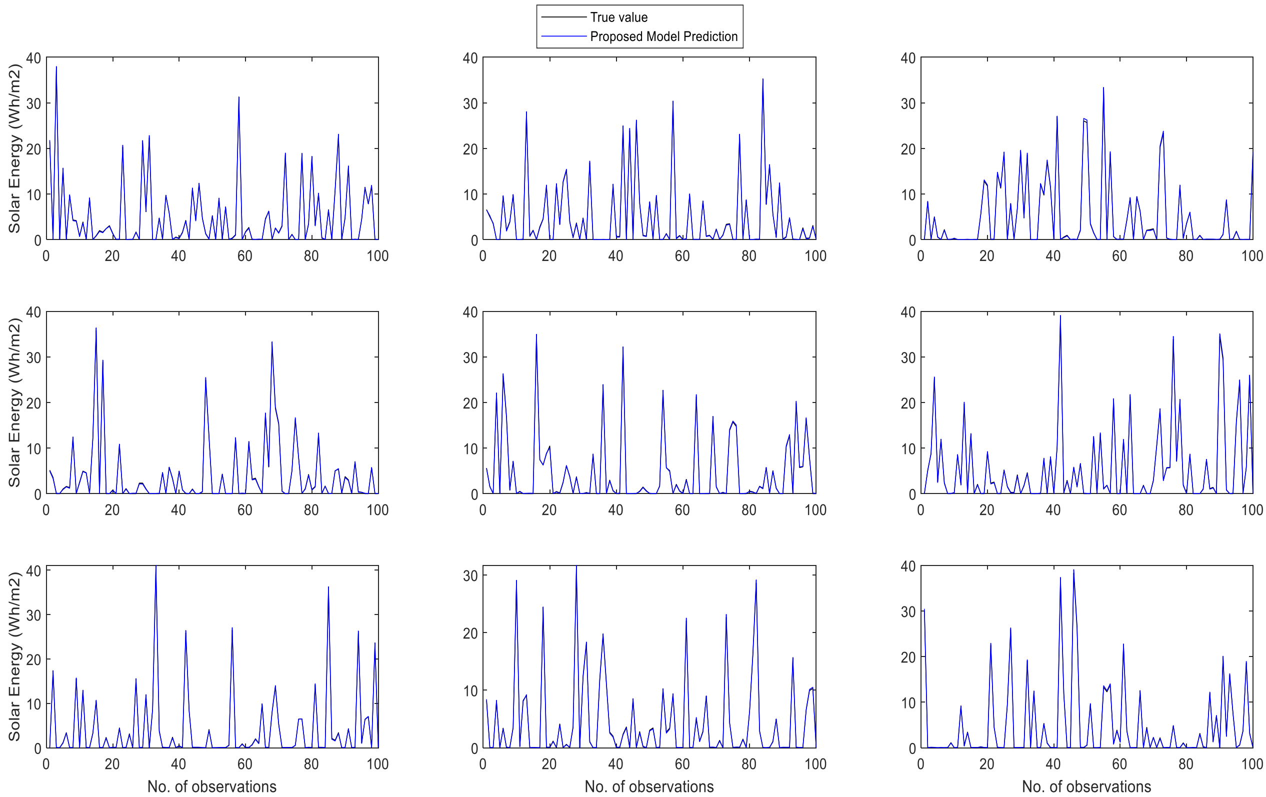

Fig. 7. Prediction results of proposed model.

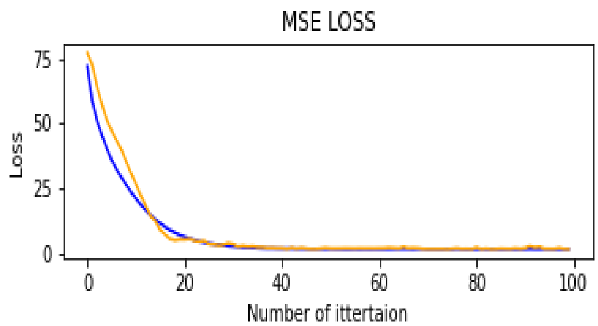

Fig. 8. Loss function graph of proposed deep learning model.

3.4 Performance Analysis Parameters.

The analysis of the proposed model is done under error based and coefficient based parameters. These parameters include:

Root Mean Square Error (RMSE). It is a quantitative measure that computes the square root of mean of all the errors. It is computed over the predicted (Pr) and Actual (Ac) values. RMSE computation is shown in Eq. 1.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{N} \frac{(Ac_i - Pr_i)^2}{N}}. \qquad (1)$$

Mean Absolute Error (MAE). MAE computes the average magnitude of difference between actual (Ac) and predicted (Pr) values. Eq. 2 shows the computation of MAE.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |Ac_i - Pr_i|. \qquad (2)$$

Mean Squared Error (MSE). MSE is another error measure that computes the mean of the square of difference of actual (Ac) and predicted (Pr) values. Eq. 3 shows the computation of MSE.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (Ac_i - Pr_i)^2. \qquad (3)$$

Where, N is number of observations,

Ac is set of actual values,

Pr is set of predicted values.

Coefficient of Determination (R^2). R^2 is a correlation based predictor that identifies the predicted value is associated with the outcome or not. It is computed as the square of coefficient of correlation. Its computation is shown in Eq. 4.

$$R^2 = \frac{\sum_{i=1}^{N} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}. \qquad (4)$$

Where, y is the observed value set,

$\hat{y}$ is the fitted value,

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$\bar{y}$ is the mean value.

4. RESULTS AND DISCUSSION

In this paper, a deep learning based intelligent method is proposed for solar energy prediction. The model is applied on the dataset taken from real and open environment. The collected features are affected by environmental and atmospheric variations. The dataset features, designed model and associated parameters are already described in the previous section. In this section, accuracy and performance of the proposed model is compared with the persistent MLP method of prediction. Performance evaluation parameters as given in Section 3.4 are used for the comparison of these two models.

Fig. 9 shows both the MLP and proposed model solar energy prediction results against true values. The experimental results are provided in this figure for 100 random observations of testing set. Fig. 9 shows that the results of MLP based method are quite close to true values. Though MLP model provides good predictions, the results obtained from proposed neural network are more accurate and precise. The zoomed view of Fig. 9 is shown in Fig. 10 to get a clear insight about the three different values i.e., true value, MLP prediction and proposed model predictions. This line graph clearly shows that the predictions achieved from proposed model are very close to the true values throughout all the observations.

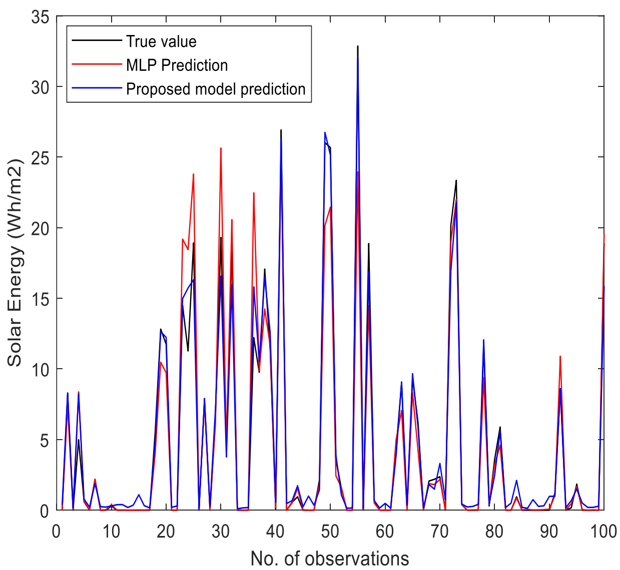

Fig. 9. Comparison of predicted solar energy using proposed model and MLP model.

Table 2 shows the value of different errors obtained against existing persistent MLP and proposed neural network model. It shows that the MSE, RMSE and MAE values achieved by the proposed model are less than that of persistent MLP. The MSE value of persistent MLP model is quite high i.e. 6.781 whereas the proposed model achieved the accuracy with MSE of only 1.88. Similarly, the proposed model achieved RMSE and MAE values of 1.37 and 0.728 (Wh/m^2) respectively.

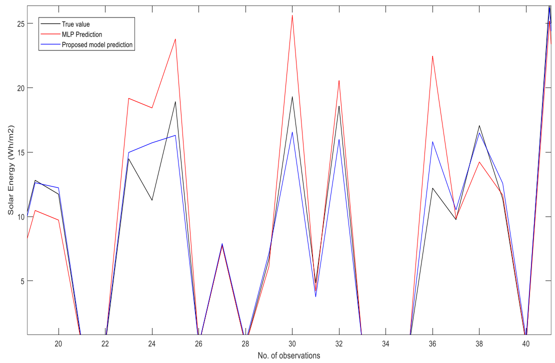

Fig. 10. Closer view of the predictions obtained from proposed model and MLP with true value.

There is an improvement of 1.234 and 0.4 (Wh/m^2) in RMSE and MAE values using the advanced proposed model. The goodness-of-fit value obtained using R^2 measure in the proposed model is 0.968 which is also higher than the existing model. Even though the training time of proposed model is comparable to MLP, but the significant improvement of 7.5% in R^2 value confirms the excellent performance of the proposed neural network model in predicting solar generation.

Table 2. Comparison of MLP and proposed model w.r.t. numerical values of the accuracy measures.

Model	Persistent MLP	Proposed Model
MSE (Wh/m^2)	6.781	1.88
R^2	0.893	0.968
MAE (Wh/m^2)	1.127	0.728
RMSE (Wh/m^2)	2.604	1.37
Training Time (sec)	20	21

5. CONCLUSION

In the field of solar energy forecasting, researchers have mainly focused on developing efficient models for solar radiation prediction. There are very few studies that have worked upon solar power/solar energy generation prediction. Direct prediction of solar generation helps in providing prerequisite information about the installation cost of solar panels. In this paper, an advanced deep learning based neural network model is presented for accurate prediction of solar energy. The proposed model acquired 11 different features related to solar energy generation to produce the most accurate predictions. The critical relationship between these features is analyzed carefully in this research which becomes the foundation for designing the proposed model. The predictive analysis of this model is done using RMSE, MAE, MSE and R^2 parameters. The comparative analysis of the model is done against persistent MLP model. The analysis results identified that the performance of proposed model is much better than the baseline model (MLP). RMSE, MAE and MSE values obtained for the proposed model are 1.37, 0.728 and 1.88 (Wh/m^2) respectively. The R^2 value obtained for the proposed neural network is 96.8%, which defines the higher predictive power of the model. These results show that the proposed model has the tendency to improve the accuracy and reduce the error in solar energy prediction by a great amount.

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