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AN IMPROVED ACCURACY FOR THE FORECASTING OF POWER GENERATION OVER A LONG-TERM HORIZON

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ABSTRACT

Renewable energy becomes increasingly popular in the global electric energy grid, improving the accuracy of renewable energy forecasting is critical to power system planning, management, and operations. However, this is a challenging task due to the intermittent and chaotic nature of renewable energy data. To date, various methods have been developed, including physical models, statistical methods, artificial intelligence techniques, and their hybrids to improve the forecasting accuracy of renewable energy. Hence this research proposed to hybridize two strong deep learning algorithms where modeling of more complex functioning is allowed by the use of multiple layers of abstraction in order to come up with a powerful forecasting model to predict solar power generation over long term horizon. Finally, the Deep Neutral Network and Long-short Term memory Network (DNN-LSTM) method can generate predicted solar energy consumption in a fully connected hierarchy. The proposed DNN-LSTM model achieved Mean Square Error (MSE) of 0.00825 and MAE of 0.00100 respectively. This is by far the lowest value when compare against the existing model i.e MLSHM which has MSE of 0.05700 and MAPE of 0.00695, LSTM which has MSE of 0.0536 and MAE of 0.0037 and Gated Recurrent Unit (GRU) which has MSE of 0.03460 and MAE of 0.00243 respectively. Thus, the proposed DNN-LSTM have clearly enhanced the forecasting accuracy as against all the existing models that was used for the evaluation and achieved the lowest values in terms of validation of MSE and MAE.

Keywords: Accuracy, Energy, Forecasting, Prediction, Power

INTRODUCTION

Power forecasting of renewable energy power plants is a very active research field, as reliable information about the future power generation allow for a safe operation of the power grid and helps to minimize the operational costs of these energy sources Gensler et al., (2016).

As renewable energy becomes increasingly popular in the global electric energy grid, improving the accuracy of renewable energy forecasting is critical to power system planning, management, and operations. However, this is a challenging task due to the intermittent and chaotic nature of renewable energy data. To date, various methods have been developed, including physical models, statistical methods, artificial intelligence techniques, and their hybrids to improve the forecasting accuracy of renewable energy. Among them, deep learning, as a promising type of machine learning capable for discovering the inherent nonlinear features and high-level invariant structures in data, has been frequently reported in the literature (Wang, et al., 2019). According to Mocanu et al., (2016), energy forecasting can be grouped into either one of these three groups, they include (i) short term forecast usually ranging from a day to a week (ii) medium term forecast usually ranging from a week to a year and (iii) long term forecast usually ranging from a year and above.

Different approaches have been proposed in the literature, one possible way to categorize different approaches is to sort them by their forecasting horizon. Another possibility to group forecasting techniques is by their methodical foundations. A typical categorization would thereby be physical models, such as Numerical weather prediction (NWP) in combination with wind or solar power curves, machine-learning models, such as artificial neural networks, and statistical models, e.g., the ARIMA model. Artificial Neural Networks (ANN) is a popular method for forecasting tasks. The applied architectures range from simple multilayered perceptron (MLP) to more complex networks such as recurrent neural networks or time delay neural networks. Different network architectures have been applied to forecast renewable energy sources. The study in Zhang et al., (1998) shows different network topologies with good performance in forecasting tasks. Various algorithms have been reported in the literature to provide accurate renewable energy predictions for the next few minutes to the next few days. They are usually divided into four categories: physical methods, statistical models, artificial intelligence techniques and their hybrid methods (Hodge et al.,2018).

Physical methods are based on numerical weather prediction (NWP) models that simulate the atmospheric dynamics according to physical principles and boundary conditions. NWP models contain limited area models, such as fifth-generation meso scale model and high-resolution rapid refresh, and global models, e.g., global forecast system and integrated forecast model. Many meteorological and geographical information, including temperature, pressure, jaggedness and orographic, are considered as input to NWP. Although physical methods are efficient in forecasting atmosphere dynamics, they require large computational resources because a lot of data is needed for calibration (Wang et al., 2019).

Statistical models aim to uncover the mathematical relationship between online time series data of renewable energy. Auto regressive moving average, Bayesian approach, Kalmanfilte, Markov Chain model and gray theory were widely adopted in the literature. However, most of the existing statistical models for renewable energy forecast are formulated as a linear models that limit their ability to deal with more challenging prediction problems with longer forecasting time horizons (Wang et al., 2019).

With the development of soft-computing technique, artificial intelligence based forecasting models always provide a more promising performance than physical methods and statistical approaches due to their potential abilities for data-mining and feature-extracting Daut et al., (2017). A detailed comparison of the existing models for renewable energy forecasting was given in the literature, showing that each single model has advantages and disadvantages. Therefore, the papers in the fourth category suggest how to combine different forecasting methodologies to take advantage of the benefit of each individual method. However, the aforementioned methods for renewable energy forecasting generally adopt shallow models as their core of learning principles.

Deep learning, as a promising branch of machine learning, has attracted much attentions in recent years due to three major attributes., unsupervised feature learning, strong generalization capability and big-data training, compared with shallow models Wang et al., (2019). Hence, in order to improve the forecast accuracy as suggested by Gensler et al., (2016) this study puts forward a hybrid deep learning algorithm using deep neural network and LSTM recurrent neural network to forecast medium to long term solar power generation (solar farm).

Related Work

The world has faced a serious depletion problem of natural resources and a climate change problem due to an overuse of fossil fuels, and, thus, we need to take more alternative energy sources, so called 'renewable energy sources' fuels. Penetration of renewable energy sources into main grid has gradually increased in recent years and this penetration is expected to increase more rapidly until 2030 (Jang et al., 2016). Focusing on the solar energy in South Korea, the penetration ratio of solar energy among all available energy sources is expected to gradually increase up to 14.1% until 2035 Jang et al., (2016). Currently, the world has been actively pursuing the development of renewable energy technologies. Photovoltaic (PV), concentrated solar power (CSP), and wind turbines are valuable technologies of alternative energy resources that enable harvesting energy from solar radiation, solar thermal and wind energy, respectively.

As renewable energy becomes increasingly popular in the global electric energy grid, improving the accuracy of renewable energy forecasting is critical to power system planning, management, and operations. However, this is a challenging task due to the intermittent and chaotic nature of renewable energy data. To date, various method shave been developed, including physical models, statistical methods, artificial intelligence techniques, and their hybrids to improve the forecasting accuracy of renewable energy. For example Gensler et al., (2016) proposed Deep Learning for Solar Power Forecasting using Autoencoder and LSTM Neural Network and compare it with MLP, LSTM, AUTO LSTM and DBN, the experimental results shows that Deep Learning algorithms have a superior forecasting performance compared to ArtificialNeural Networks and other reference models such as physical models. Similarly, Jawaid and Nazir Junejo, (2016) Predict Daily Mean Solar Power Using Machine Learning Regression Techniques and evaluate it to ANN and Linear Regression, the findings revealed that incorporation of azimuth and zenith parameters in the model significantly improves the performance.

Also Fouilloy et al., (2018) proposed Solar irradiation prediction with machine learning and compared the forecasting performance against ARMA, MLP and bagged regression tree, for the weak variability, auto-regressive moving average and multi-layer perceptron are the most efficient, for a medium variability, auto-regressive moving average and bagged regression tree are the best predictors and for a high one, only more complex methods can be used efficiently. One of the most recent studies of wind power forecasting was proposed by Liu et al., (2019) in which a Weight-Varying Ensemble Method was utilized for Short-term Forecasting of PV Power Output and evaluate the empirical results to Generalized Regression Neural Network (GRNN), Extreme Learning Machine Neural Network (ELMNN) and Elman Neural Network (ElmanNN), Results show that the WVE model achieved a higher accuracy with mean absolute percentage error (MAPE) of 5.17%, 5.26%, 5.49% and 5.82% for four types of data. Yagli et al., (2019) proposed Automatic hourly solar forecasting using machine learning models and evaluate it to SVR, LASSO and GLM, it is found that tree-based methods consistently perform well in terms of two-year overall results. This model has an effect of small change in data can cause a large change in the structure of the decision tree causing instability and also sometimes its calculations are more complex compared to other algorithms. Also, Feng et al. (2020) uses Machine learning models to quantify and map daily global solar radiation and photovoltaic power and evaluate the results against ELM,SVM, GRNN and AE. The research confirms the effectiveness of the PSO-ELM for solar energy modeling, particularly in areas where in-situ measurements are unavailable. However, the aforementioned methods for renewable energy forecasting generally adopt shallow models as their core of learning principles. Therefore, this paper proposed DNN-LSTM model for forecasting power generation since most of the reviewed existing work recommended the use of hybridization of two strong deep neural networks that will give more accurate results than the other existing algorithms

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METHOD

This section describes our proposed method compared to previous methods. We use actual data composed of several input variables. The DNN-LSTM model learns the input data preprocessed every sub hourly by the sliding solar algorithm. The spatial characteristics of a multivariate time series variable are extracted from the hidden layers of the DNN layer and passed to the LSTM layer with the noise removed. The LSTM layer models the irregular time information using the transmitted spatial features. Finally, the DNN-LSTM method can generate predicted solar energy consumption in a fully connected hierarchy. The energy consumption values generated by the prediction model are evaluated and analyzed by the error metrics (MAE AND MSE).

Architecture of proposed method

The deep proposed method for predicting solar energy consists of a series connection of DNN and LSTM. The model can extract complex features among multiple sensor variables collected for solar energy demand forecasting and can store complex irregular trends. The design of DNN-LSTM can be variously modified according to the type and parameter adjustment of the layers constituting the network. The DNN-LSTM used in this study consists of Input layer, Hidden layers, LSTM layer and Fully Connected layer and LSTM Regression output layer. Each layer can adjust the number of filters, the kernel size, and the number of strides. Adjusting these parameters can affect learning speed and performance depending on the characteristics of the learning data

Stage 1. Deep Neural Network Stage

First, the upper layer of the proposed deep learning consists of deep neural network. The DNN layer can receive various variables that affect solar energy consumption such as voltage, intensity, and sub-metering. The deep neural network consists of an input layer that accepts sensor variables as inputs, an output layer that extracts features to LSTMs recurrent neural network, and several hidden layers. The deep net layer operates on the incoming multivariate time series sequence and passes the results to the next layer. The deep net operation emulates the response of individual neurons to visual stimulation. Each neuron processes energy consumption data only for the receptive field. This operation can reduce the number of parameters and make the proposed DNN network deeper thus becoming deep net. The DNN uses a hidden layer that combines the output of a neuron cluster in one layer into a single neuron in the next layer which reduces the space size of the representation to reduce the number of parameters and network computation costs.

Stage 2. Long Short-Term Memory Stage

The LSTM stage which is the lower layer of the DNN-LSTM architecture, stores time information about important characteristics of power demand extracted through the DNN. The LSTM provides a solution by preserving long-term memory by consolidating memory units that can update the previous hidden state. This function makes it easy to understand temporal relationships on a long-term sequence. The output values from the previous DNN layer are passed to the gate units. The LSTM network is well suited for predicting power demand by addressing explosive and vanishing gradient problems that can occur when learning traditional RNNs. The three gate units are a mechanism for determining the state of each individual memory cell through multiplication operations. The gate unit consists of input, output, and forget gate, depending on the function. The memory cells that make up the LSTM update their states with activation of each gate unit that are controlled to a continuous value between 0 and 1. The hidden state of the LSTM cell, ht, is updated every t step. Using LSTM cells provide superior performance through time information modeling of signals and provide leading edge results in predicting solar energy consumption. The last layer of the deep DNN-LSTM is made up of fully connected layers. This can be used to generate the power consumption over a certain period of time. The overall architecture of the proposed model is depicted in Figure 1.

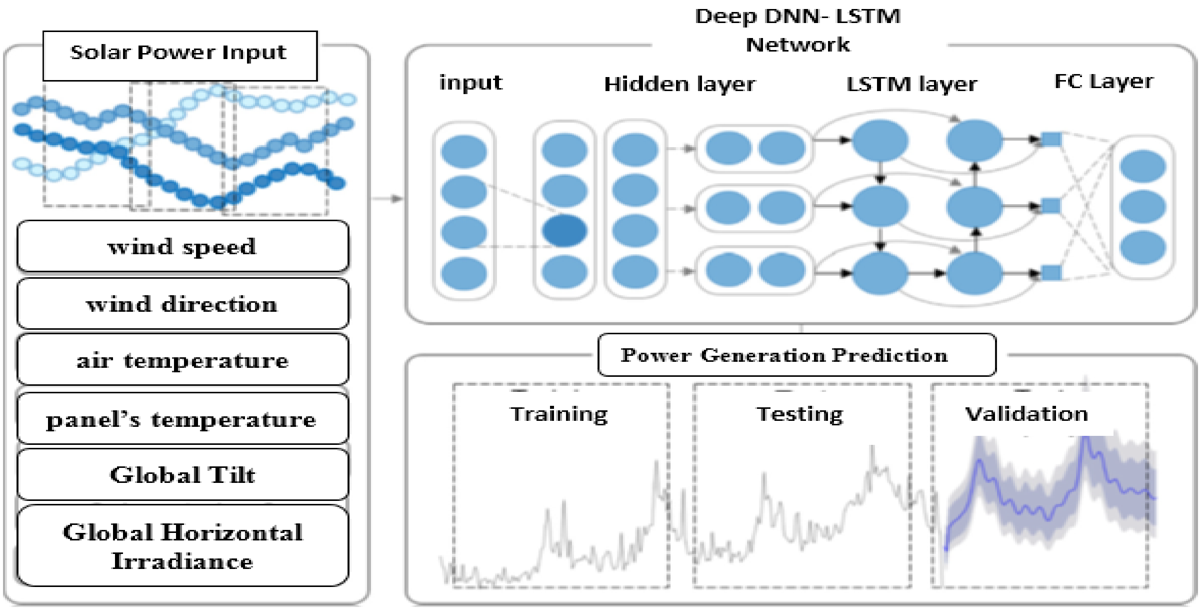

Figure 1: Proposed hybrid-based point forecaster for solar power generation.

Dataset Description and Processing

In this paper Shagaya dataset will be use. The reason of using Shagaya as the source of data is because most of the local sources are not having stored dataset that is enough to be used for this research. I tried getting primary datasets but was not possible which forced me to use the secondary dataset I found internet.

The time series datasets used in this research were collected online from kaggle repository portal. It contains solar power data for Shagaya in Kuwait. The dataset was collected from Shagaya Renewable Energy Park in Kuwait from May 5, 2017, to June 30, 2018. The solar PV plant in Shagaya is about 10 MW capacity and consists of two sub-plants of two different PV technologies, Polycrystalline solar panel (Poly-SI) and Thin film solar cells (TFSC). The Shagaya dataset includes the total solar power generated from each sub-plant (kW) as well as the meteorological data of the site which are Global Horizontal Irradiance (GHI) (kW/m2), Global Tilt Irradiance (GTI)(kW/m2), solar speed (m/s), solar direction (°), air temperature (°C), and panel's temperature (°C). The time series dataset is available in different solutions, i.e., five-minute, sub-hourly, hourly, daily, and monthly. In this regard, the paper adopted the sub hourly dataset to forecast the solar power generation capacity for the coming months. The reason of choosing the sub-hourly dataset is because the hybrid algorithms performance needs large data to show the improvement of accuracy using deep neural network. The other forecasting algorithms performs better using the available time series dataset

Choice of Metrics

In order to comprehensively and extensively evaluate the effectiveness of the proposed forecasting framework, four widely-used performance metrics in statistics, i.e., mean absolute error (MAE), mean square error (MSE) and error correlation was used to ascertain the best performing model.

RESULTS AND DISCUSSION

In this research the accuracy of the estimated forecasts of the proposed model will be compared with the other models to ascertain which model gives a more accurate forecast through the use of MAE, MSE, and Correlation Error (R). The main purpose of the graphs obtained from the simulation is not to be directly analyzed, but rather give the reader an overview of how the trend continues. The proposed DNN-LSTM model has MSE of 0.00825 and MAE of 0.00100 respectively. This is by far the lowest value when compare against the existing model i.e MLSHM which has MSE of 0.05700 and MAPE of 0.00695, LSTM which has MSE of 0.0536 and MAE of 0.0037 and GRU which has MSE of 0.03460 and MAE of 0.00243 respectively. Thus, the proposed DNN-LSTM have clearly enhanced the forecasting accuracy as against all the existing models that was used for the evaluation by achieving the lowest values in terms of validation MSE and MAE. Similarly, in terms of correlation error R, the proposed model obtains a regression value close to 1 which clearly interpret that the model was perfectly fit for the target data used in both the training, testing and validation phase respectively. In general, the proposed model demonstrate superiority in forecasting long term solar power generation model with high accuracy as against the state of the art as can presented in the following sections.

Evaluation of the Predictors

From the results of our simulation, we obtain the following plots which will demonstrate how perfectly fit is our model. In order to validate the developed network, the Error histogram was used. Figure 2 shows the regression graph for the proposed model; this shows how accurately the proposed trained model fits the dataset. It was observed that the value of R is close to 1 (good) which demonstrate that the model prediction is very close to the actual dataset. If it was close to zero (bad) then it shows that the model completely fails in making a correct prediction. In our own case, the overall correlation error as shown in Figure 2 is 0.9985 which so close to 1, this clearly indicate that the model prediction was close to the actual test which demonstrate a good and reliable prediction by the proposed model.

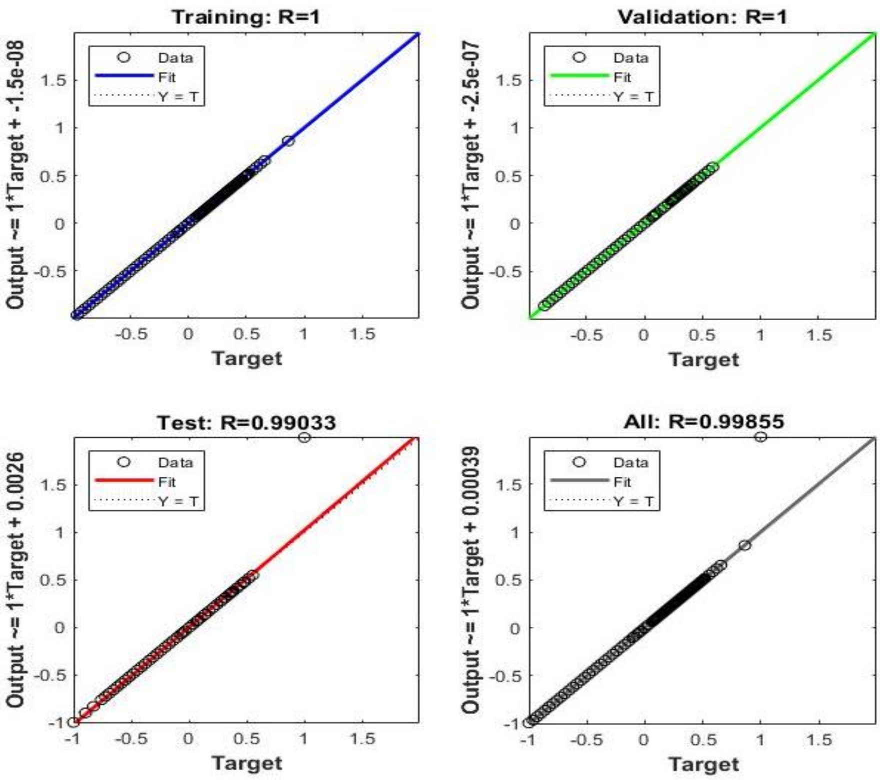

Figure 2: Error regression on forecast vs. actual

The training algorithm used in this research work to train the proposed model is Bayesian regularization back propagation algorithm which converged after 363 epochs, and it showed stability (no increase after converging) and no overshoot (no increase before converging), as shown in Figure 3.

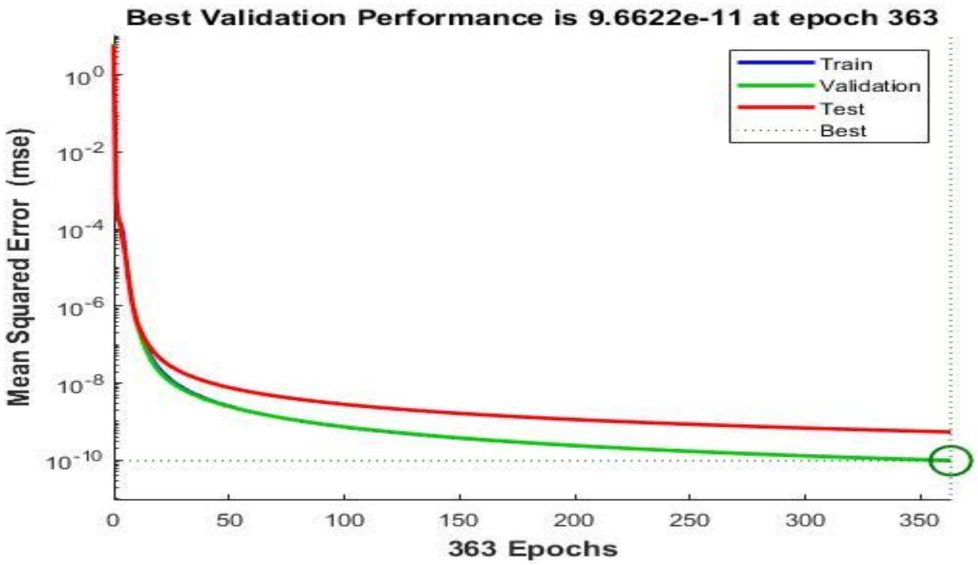

Figure 3: Training Performance for the proposed Model

In MATLAB, the default metric for evaluating training performance is the Mean Square Error (MSE), From Figure 3 above, the best training performance in MSE was 9.6622E-11, This indicate a very good training performance because for MSE, RMSE and MAE, the smaller the value obtained by a forecasting model, the better the performance being achieved, hence in this experiment the MSE is very small when compare to the existing work, this further proves the efficiency of the proposed model against the existing works. Moreover, Figure 4 displays the observed values and the corresponding forecast values while Figure 5 shows the forecasting trend of the times series data for the solar power.

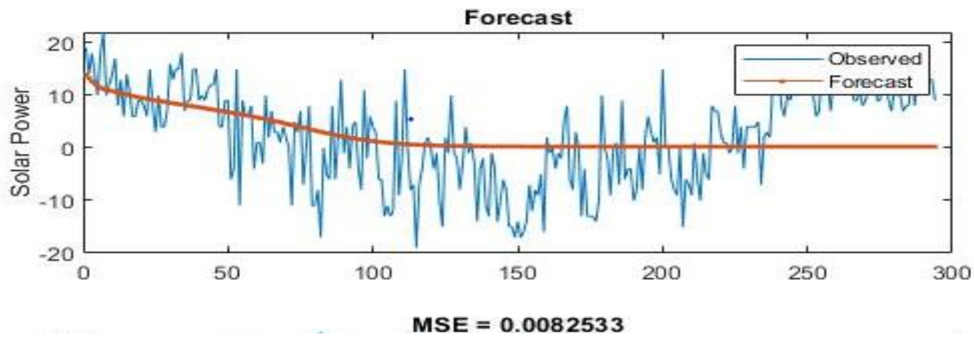

Figure 4: Observed vs forecast

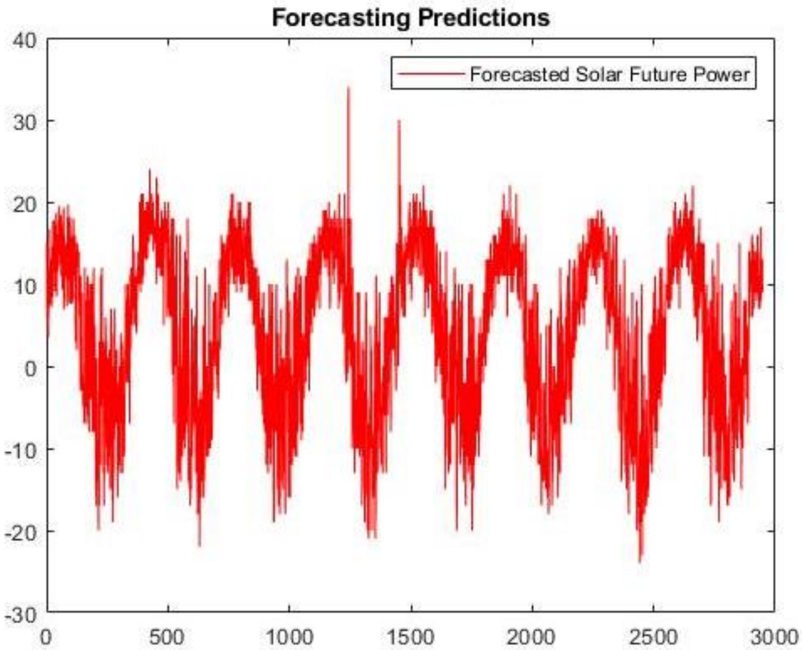

Figure 5: Forecasting Trend

Table 1 below also illustrates how the performances of the proposed hybrid approach compare with those of the existing model for the forecast of solar power. As stated earlier, for the MSE and MAE, the smaller the value, the better the performance.

Table 1: Performances of the proposed model with existing models in terms of MSE, and MAE

	Proposed Model	MLSHM	LSTM	GRU
MSE	0.00825	0.05700	0.0536	0.03460
MAE	0.00100	0.00695	0.0037	0.00243

From Table 1 above, for the Validation MSE and MAE, the smaller the value the better the accuracy, in this case, the proposed DNN-LSTM model has MSE of 0.00825 and MAE of 0.00100 respectively. This is by far the lowest value when compare against the existing model i.e MLSHM which has MSE of 0.05700 and MAPE of 0.00695, LSTM which has MSE of 0.0536 and MAE of 0.0037 and GRU which has MSE of 0.03460and MAE of 0.00243respectively. Thus, our proposed DNN-LSTM have clearly enhanced the forecasting accuracy as against all the existing models that was used for the evaluation by achieving the lowest values in terms of validation MSE and MAE. Thus, our proposed model demonstrate superiority in forecasting long term solar power generation model with high accuracy as against the state of the art. To further demonstrate our results, Fig 6 shows the graphical representation of the simulation results obtained in this work.

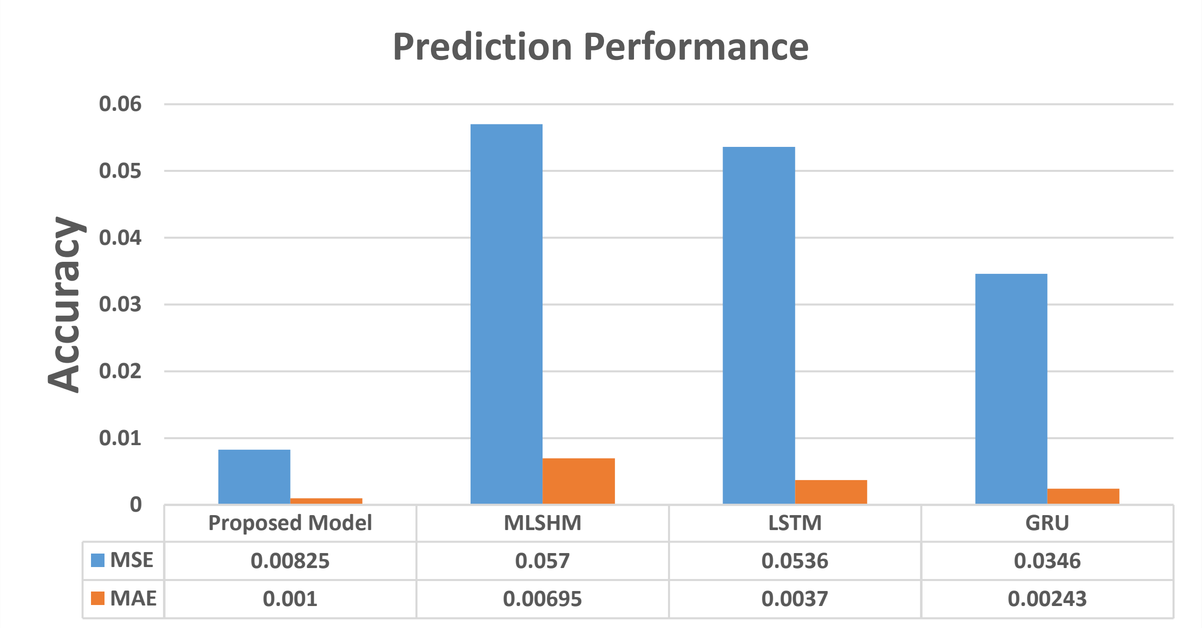

Figure 6: Prediction Performance

Based on Figure 6 above, the proposed model achieved the lowest value in terms of MSE and MAE when compare with the other models, this shows that our, proposed model achieved the best prediction accuracy, thus this research have significant improvement against the previous studies.

CONCLUSION

This paper proposed to hybridize two strong deep learning algorithms where modeling of more complex functioning is allowed by the use of multiple layers of abstraction. In order to come up with a powerful forecasting model that will improve the prediction accuracy of solar power generation over long term horizon. These approaches are being applied recently in the context of energy prediction. The proposed concept uses actual data composed of several input variables. The DNN-LSTM model learns the input data preprocessed every sub hourly. The spatial characteristics of a multivariate time series variable are extracted from the hidden layer of the DNN and passed the output to the LSTM layer with the noise removed. The LSTM layer models the irregular time information using the transmitted spatial features. Finally, the DNN-LSTM method can generate predicted solar energy consumption in a fully connected hierarchy.The predictions were made in sequence at sub-hour resolution over a medium-long term time horizon (>1 week). Overall, the proposed hybrid neural network model presented in this analysis perform well in forecasting solar power for medium to long term time horizon. The future work should concentrate on using other machine learning models to see whether accuracy for forecasting solar power generation will increase more than that of the existing models.

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