Solar Power Forecasting for Smart Grid System by Using Deep Learning Techniques

Shambvu Prasad Mandal [a], Tri Ratna Bajracharya [b], Prasis Poudel [c]
[a, b] *Department of Mechanical Engineering, Pulchowk Campus - Institute of Engineering, Lalipur, Nepal*
[c] *Department of Electronics and Computer Engineering, Mokpo National University, Mokpo, South Korea*
Corresponding Email: [a] shamvumandal@gmail.com, [b] triratna@ioe.edu.np, [c] er.prasis@gmail.com

***Abstract*— This paper presents Solar Photovoltaic (PV) power modeling using polynomial regression and artificial neural deep learning techniques. This method has been developed and validated using a 35.58 kWp Solar PV system installed inside the K3 substation of Singhdarbar, Kathmandu Nepal. In this study, first, the PV power data is modeled by using two different neural networks namely multilayer neural network (MNN) and long short – term memory networks (LSTM) are examined. For PV power data modeling using deep learning techniques, all recorded data is used and parted into two as 90% for training and 10% for prediction in the various structure of both deep learning techniques in order to find the best deep learning structure in terms of low loss error. With these best models, prediction results show the long short term memory network has a better performance compared to the multilayer neural network.**

Keywords—solar photovoltaic power, polynomial regression, deep learning technique, multilayer neural network, long short-term neural network

I. Introduction

Energy is an essential source for human lives and a key factor for the development of a country. Due to the changing of the world like industrialization, modernization, population growth and living standard of people, demand for energy, especially electrical energy demand has increased over the years. In recent times, renewable energy installation has become a significant solution to this problem since it has minimal environmental issues. Solar photovoltaic (PV) energy has experienced enormous growth in electricity generation. In the last few years, the installation of PV systems increased rapidly in on-grid and off-grid systems. Solar PV power is the outcome of the solar irradiance which is absorbed by the PV panels. There are several parameters, including weather parameters that affect solar irradiance. The past values of solar irradiance and weather data are very important to model an accurate solar forecasting model and build a profitable power plant.

Energy is an important development indicator, which provides vital inputs for survival and economic development. Energy supply and consumption are still in a traditional state in Nepal. At present, the renewable energy generation capacity of the country is still significantly very low due to technological and economic barriers. But the average efficiency of renewable energy technologies is good in performance and also environmentally safe. As data recorded in 2016 only seventy-six percent of people have access to Electricity in Nepal [1]. Out of which fifteen percent of the rural population gets electricity from the off-grid renewable energy source as of National census 2011. Providing access to electricity to a large chunk of rural populace in Nepal has traditionally been a daunting exercise, because of its huge capital investment, geographic difficulties, lack of proper infrastructure in development of hydropower work, and where decentralization generation is only way to electrify, where extension of national grid makes no sense because of need of long transmission lines for less power consumption in a rural village, Photovoltaic (PV) Solar System based off-grid renewable energy is likely to be the key for reaching rural population which still lacks access to electricity.

Artificial intelligence-based forecasting techniques have been used successfully in many areas such as finance and banking-insurance [1] for analysis of exchange rate evaluation, stock price forecasting and predictions, industrial and agricultural production, and medical sectors [2][3]. Numerous forecasting modeling technique is also applied in PV power output: artificial neural network (ANN) based model [4], time series model [5], and time trend extrapolation model [6]. Among these models, Deep Learning techniques based models have more accurate prediction results compared to other methods.

In this paper, various structures of the multilayer neural and long short-term memory networks [7] have been tested to model PV power output using a 35.58 kWp Solar PV system installed inside the K3 substation of Singhdarbar, Kathmandu Nepal. The purpose of this work is to examine the various PV modeling methods for the grid energy management system which can be deployed in Nepal.

This paper is organized as follows; the experimental setup for the study is described in section II. Research methodology and experimental results are explained in section III. Finally, the conclusion is stated in section IV.

II. EXPERIMENTAL SETUP

The PV plant contains a 35.58 kWp Solar PV system installed inside the K3 substation of Singhdarbar, Kathmandu Nepal. The power-related parameters of the PV module used in this study are given in Table 1. This system is installed with a climate data collection device and a remote power data acquisition device. The climate data collection device has an anemometer for the wind speed measurement, and temperature sensors for each PV module to measure the ambient temperature. And pyranometers are used to measure solar irradiance. Google map images and used devices are shown in Figures 1 and 2 respectively.

Google Map Image of K3 substation, Ktahmanu Nepal

Data logger at Singhdarbar, K3 substation, Kathmandu Nepal

TABLE I. TECHNICAL SPECIFICATION OF PV MODULE

1	Rated power	280.0 W(0/+5w)
2	Rated voltages	31.4V
3	Rated current	8.91 A
4	Open circuit Voltage	39.3 V
5	Short Circuit Current	9.38 A

III. METHODOLOGY AND EXPERIMENTAL RESULT

The methodology followed to develop optimal machine learning models for PV power predictions a training phase (to effectively apply a learning technique to a performance function) and a testing phase (to assess the prediction accuracy performance). More specifically, in order to capture the systematic behavior of a PV system and to design optimal machine learning models a sequence of training and validation stages must be performed by varying the input parameters (features), training duration and architectural parameters of the devised models. It is important to mention that this work focuses on comparing and improving the accuracy of derived machine learning models (as the training and testing were performed on historical data) shown in figure 3.

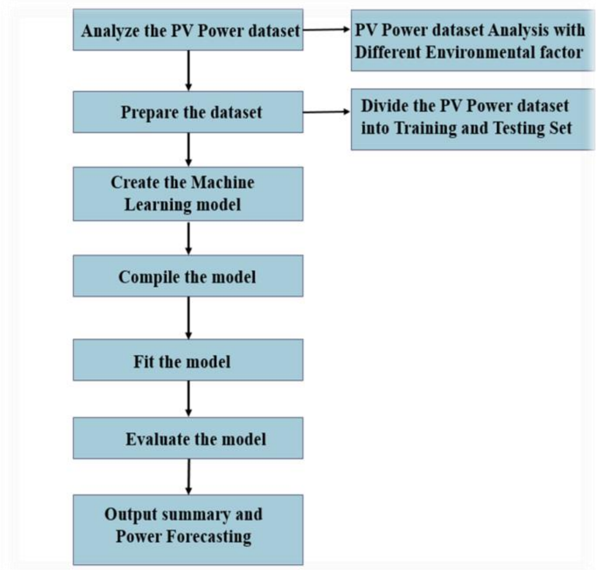

Fig.3. Block diagram showing Methodology for forecasting PV data using machine learning algorithms

In this work, the recorded historic PV power data was modeled by using deep neural network mainly multiple neural networks (MNN) and Long short term memory (LSTM) algorithm analyzing with each different structure to get the best modelling prediction result having a minimum root mean square error (RMSE) shown in equation 1.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(\widehat{P_i} - P_i\right)^2}{n}} \ldots\ldots\ldots\ldots (1)$$

Here, $\widehat{P}_1, \widehat{P}_2, \widehat{P}_3, \ldots\ldots\ldots\ldots\ldots.\widehat{P}_n$ are predicted solar power and $P_1, P_2, P_3, \ldots\ldots\ldots\ldots\ldots.P_n$ are measured values where n is the no of observations.

Figure 4 below shows an overview of the applied deep learning algorithms performed for each model. The solar PV power data is hourly based on four-month data. The whole data set is divided into 90% and 10% to train and test in the various model structure.

```
Load PV Power data from csv file
for each forecast do
  filter data based on availability;
  arrange dataset in array;
  partition the dataset into 90% training and 10% test set;
  define a parameter set (e.g. look back);
  define model structure
    for each model structure do for
      configure model;
        model fit;
        evaluate the model using loss value;
        predict values for the training set;
      end
        calculate the average RMSE on the training sets;
    end
    determine optimal hyper parameters (i.e. lowest RMSE);
    test model on all test data with optimal hyper parameters;
    evaluate the model on the test set (i.e. the 10% of data);
end
```

Fig.4. Flow Chart of LSTM and MNN Deep Learning Algorithms

Detail procedure of implementing Machine Learning Algorithms for Forecasting recorded PV Data is clearly shown in figure 5.

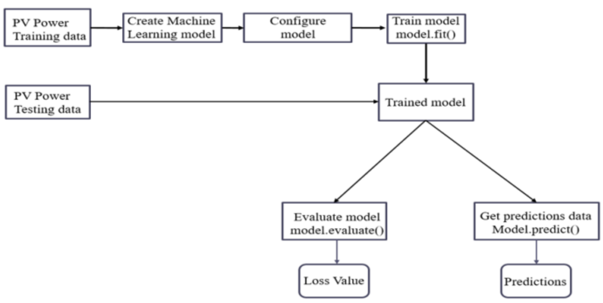

Fig.5. Implementation of machine learning algorithms for forecasting PV data in details

The input for both MNN and LSTM model is PV power output from PV modules at the K3 substation of Singhdarbar, Kathmandu Nepal. In the training process, collected whole day PV power is used to find the optimal weighting vectors. Furthermore, the best optimal neuron structures are unknown, we are trying to find the best model based on their MSE in the training stage. The training data used in this study is shown in Figure 6.

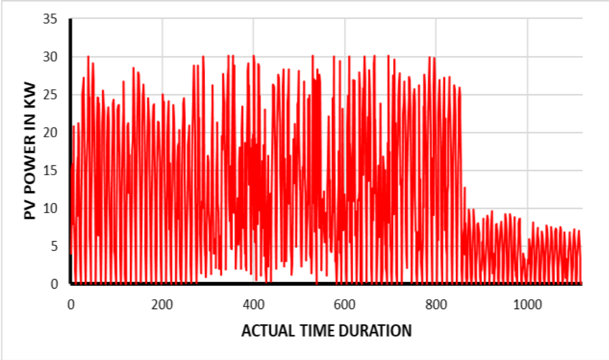

Fig.6. Recorded PV data for training and testing

To select the best optimal models in MNN and LSTM, Root mean squared error (RMSE) of both models have been evaluated in both training and testing phase. At 400 and 50 epochs for the training process of MNN and LSTM, the error is converged and the training is stopped. The RMSE obtained from different MNN and LSTM structures during the training and testing process are shown in Figures 7 and 8 respectively.

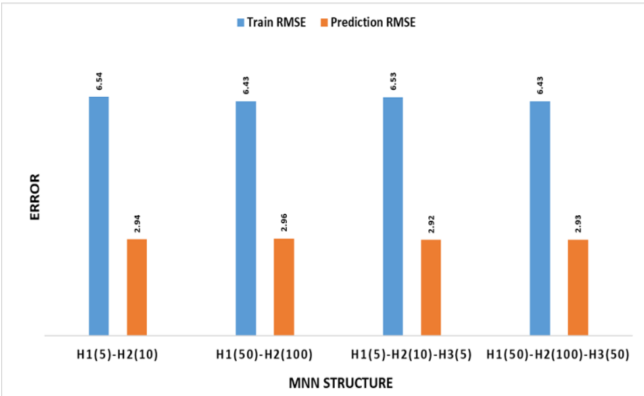

Fig.7. RMSE for different MNN structures

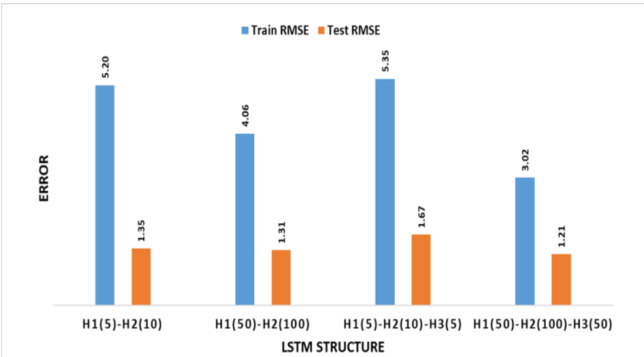

Fig.8. RMSE for different LSTM structures

From the training and testing RMSE evaluations of both MNN and LSTM model, it can be observed that the best MNN structure is with one input (In (1)) node, first hidden layer with five nodes (H1 (5)), second hidden layer with ten nodes (H2 (10)), third hidden layer with five nodes (H3 (5)), and one output node (Out (1)).

The best structure of LSTM is with one input (In (1)) node, first hidden layer with fifty nodes (H1 (50)), second hidden layer with hundred nodes (H2 (100)), third hidden layer with fifty nodes (H3 (50)), and one output node (Out (1)). Those best model structures have low error values shown in table 2 below.

TABLE II. RMSE RESULTS FROM TRAINING TWO BEST MODELS

Number of Hidden Layer	Hidden Layer Nodes	LSTM Model		MNN Model	
		Train RMSE	Prediction RMSE	Train RMSE	Prediction RMSE
3	H1(5)-H2(10)-H3(5)	5.35	1.67	6.53	2.92
3	H1(50)-H2(100)-H3(50)	3.02	1.21	6.43	2.93

The RMSE result of both the best structure of LSTM and MNN, we found that the LSTM model has a low error of 3.02 in training and 1.21 in the prediction process, which is very low in comparison to MNN.

IV. CONCLUSION

In this paper, the various structures of MNN and LSTM have been used to model PV power output. First, we try to train and select the best deep learning network structures for both models in terms of having low error output results obtained from the training data. For PV power data modelling using deep learning techniques, all recorded data is used and parted into two as 90% for training and 10% for prediction in the various structures of both deep learning techniques in order to find the best deep learning structure in terms of low loss error. With these best models, prediction results show the long short term memory network has a better performance compared to the multilayer neural network. This implies that deep learning techniques are more effective tool for solar power output prediction.

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