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Neural Network based Photovoltaic Power Generation Forecasting for Smart Grid

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***Abstract*—In the past decade power sector faces a major change due to exponential growth of population and high energy demand all over the world. The growth of renewable energy sources also increases rapidly due to high energy demand, which includes the solar energy sources (Renewable Energy Sources). The need for precise prediction of electricity demand is necessary to construct new power generation units, even it has the smaller generation capacity like micro grids and renewable energy sources in buildings or residential homes. In this paper, we have employed neural network based energy forecasting method with real time dataset for the past couple of years. The experimental results showed that the feed forward neural network model predict the solar energy generation with commanding accuracy. It is also used for cost reduction and power management in the future, which is highly suitable for consumer's energy adjustment. Further, the proposed model suggests to construct the future oriented adaptive power generation station and power transmission networks.**

***Keywords*— Artificial neural networks, Demand and supply, Load forecasting, Solar generation, Dataset.**

I. Introduction

The electricity is the most important source for all major sectors including residential, industrial and commercial. Power management, monitoring, controlling and maintain a proper balance between supply and demand power forecasting plays an essential role [1]. Due to high energy demand prosumers (service provider and consumer) have been motivated to find the alternate energy sources. As a result, the design, development and implementation of creating clean and green energy sources are found with integration of RES [2]. It is an essential need for all the countries to find the alternate sources to satisfy their energy needs. RES can be broadly classified into various types like wind, solar, bioenergy and geothermal energy. The solar supported RES saves the energy usage cost as well as increasing the clean and green energy [3]. Consequently, proper prediction is required for managing an aforementioned task. Various factors can affect the power consumption, such as the growth of population, weather conditions, energy cost and Time of Use. These parameters can be used as inputs for finding the accurate energy forecasting.

The present scenario, RES becomes more popular in all the power consumption sectors. It has high adaptability and produces the interoperability with conventional energy sources. Furthermore, it also reduces the energy consumption cost for consumers. If the solar or wind power is not consumed or excess power can sell to power grid, which gains some revenue for the consumer [4]. Smart grid faces some inconvenience like electric power balance, stability of power, reactive power compensation, power quality and phase angle due to natural calamities [5], [6], [7], [8].

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Load forecasting and RES generation models can be broadly classified into two major categories i.e., Statistical modelling and Artificial intelligence modelling. Statistical based models are multiple regressing, exponential smoothing, auto regressive, moving average, autoregressive moving average and autoregressive integrated moving average [9]. It is fully based on the dataset (historical data) to forecast the load with time series (example, solar energy forecasting). The artificial intelligence based models are artificial neural network, expert system and fuzzy logic [10].

For managing, controlling and acquiring the cost benefits to the consumer the accurate PV and solar forecasting is one of the critical tasks in power management system. The proposed neural network based forecasting model provides a solution to the aforementioned problem. The main attempt of this paper is summarized as follows:

- Day-ahead (short term) energy usage forecasting for a residential home with photovoltaic is demonstrated.
- A feed-forward neural network based forecasting model is employed to understand the future energy demand.
- A real data from Peacon Street is used for power consumption and photovoltaic generation pattern and the same dataset are used for forecasting

The remaining part of the paper is organized as follows: In section II, the characteristics of renewable energy forecasting and basic neural network model are discussed. Section III explains about the implementation and modelling of the feed forward neural network in detail. Section IV examines various scenarios with the day-ahead load forecasting results. Conclusions and future direction of the proposed work are discussed in Section V.

II. Neural Network Modelling

Some kind of machine basic cognitive process technique is adopted by neural network and it is inspired by the biological neural learning system like a human brain. The high level neural network architecture diagram is shown in Fig 1. It has an input layer, hidden layer and output layer. Both the input and output layer have a certain number of neurons. Between the input and output layer training process is performed by calculating net input using the values input (X), weight (W), bias (b) and activation function (a) through the hidden layers. Finally, through the training process output of the neural network can get a final correct output (Y).

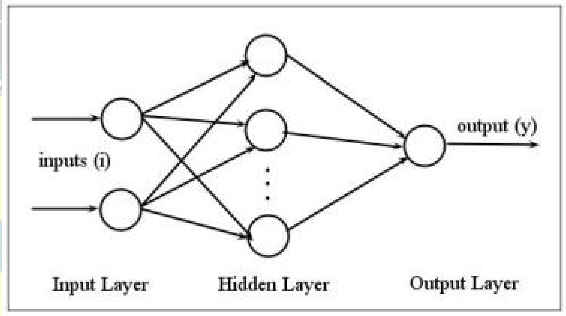

Fig. 1. Neural Network Architecture

The typical neural network with i number of input is shown in Fig. 1.

The general equation for representing the neural network

$$y = x * w + g, \qquad (1)$$

For each input $i_1, i_2, i_3, \ldots, i_n$ have its corresponding weight elements $w_1, w_2, w_3, \ldots, w_n$. The input and its weights are represented in matrix format. Bias b is added with the input and weight. The added output of $(i * p + b)$ is termed net input n_i

$$y = (i_1 * w_1 + w_2*w_2+i_3*w_3+\ldots+i_n*w_n) + b, \quad (2)$$

The above equation (2) can be represented as in the matrix format.

$$y = (I * W) + b, \qquad (3)$$

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where I denotes the number of inputs in the matrix format similarly for the weight values W. The neural output can be written as

$$a = f(I * W) + b, \qquad (4)$$

where a refers to the transfer function which produces the final output of the neuron Y.

A. Properties of Photovoltaic

The characteristics of PV and its related parameters plays vital role for controlling, modelling and forecasting. The properties of PVs and other related variables are (i). Measurement of solar irradiance, (ii). Weather condition, (iii). Reflectivity of the plates and (iv) PV cells temperature. Further, the measurement of the self-explanatory variables like outdoor temperature, cloud cover, humidity, dust, wind speed, fog, etc., depends on the solar power generation.

B. Dataset

In general, dataset plays an important role in the neural network energy generation forecasting and load forecasting. Number of records in the dataset is high to produce accurate prediction. It is also depend upon the dataset features and characteristics to get the right results. The consumers every fifteen minute energy generation profile is required for the neural network training, testing and validation process. Real time dataset is used from Pecan Street project to satisfy the required neural network [11].

C. Feed Forward Neural Network

Artificial neural network technique is broadly used for all kind of forecasting problems like stock market prediction, wind and weather prediction. The reason is due to its fast propagation behaviour and easy to implement in simulation environments. Moreover, input layer, output layer with single hidden neural network is sufficient to handle the time serious forecasting methods [9], [13].

A feed forward neural network is non-recurrent network which also contains input, hidden and output layers but the signal can travel from only one direction during the training process. Input data is passed into a first layer of a processing elements where it performs the calculations. Each process element makes it computation based upon a weighted sum of inputs. New calculated values become the new input value that feed the next layer. This process continues until it reaches the output layer with determined output.

D. Process of Training, Testing and Validation

The default transfer functions trainlm, tansig and purelin are used for input, hidden and output layers respectively. The input data can separated into three sub part of data for training, testing and validation processes severally. In general, 70% of data must be used for training i.e., if the training data is high then the neural output produces the result with high accuracy. The 15\% of the data for testing and rest of the 15% data can be used to validation [14].

III. Simulation Results

Neural network feed forward model is implemented in Matlab 2013a. The proposed model consists of input variables day and season, target variables are energy consumption with minimum number of hidden layers. The real time dataset is taken from Peacan Street and it has been processed through neural network and the observed results are graphically represented in this section.

A. Energy usage pattern with PV

The total electricity consumption of solar photovoltaic for an average house is represented both in summer and winter is shown in the graph. The Fig. 2 traces two curves for average summer and winter days: (i) The electricity consumed by a typical household electrical devices are referred as actual consumption. (ii) The electricity generated by a photovoltaic setup connected to a residential home is represented as PV generation.

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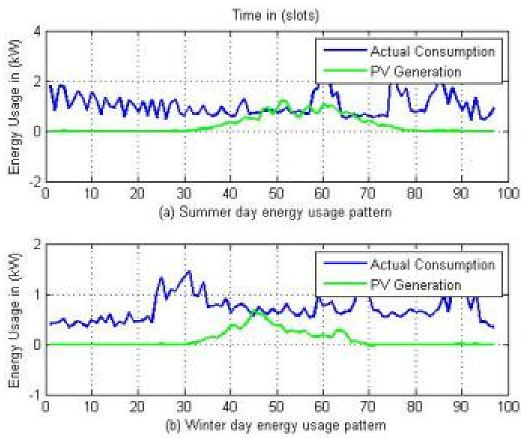

Fig. 2. Consumption and PV generation in a day

Fig. 2 shows that the amount of power being used by an average home, and generated by an average solar photovoltaic system at an interval of 15 minutes during summer days. It can be noticed that energy pattern ends at 96, its due to division of a day into 96 slots, by considering 15 minutes as 1 slot (15 minutes is referred as 1 slot thus a full day is totally divided into 96 slots). The kilowatts (kW) represented in the graph are a measure of instantaneous electricity usage/generation (e.g. an average computer uses 0.25kW of Power every hour).

If the photovoltaic generation plot is higher at any point than the Energy consumption plot, it indicates that a surplus of power is generated. When the photovoltaic generation trace is below the energy consumption trace, it implies that electricity is still generating, but this amount of power is not enough to meet the required household demands, so that there is necessity to be buying electricity from grid as per norms to make up the difference. This adds a burden since this has to be noted and the need has to be met manually. It is noticed that solar photovoltaic generation is higher during summer than winter and electricity consumption is higher during winter than summer. This is because of the fact that solar power is received to its maximum during the summer season as sun source is directly available without much dispersion. The reason for the maximum utilization of Energy during winter is the result of more usage of Room heaters to keep the room temperature high in the Cold countries.

B. Summer Day PV Generation Forecasting

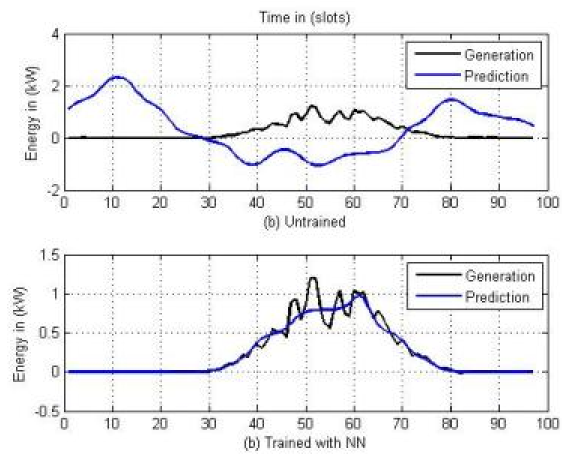

Fig. 3. Summer Day Generation Forecasting

The average electrical energy consumption and an average photovoltaic energy generation in the residential home in a summer day is illustrated in Fig. 3 A prediction of electricity consumption by the household devices in a day is also shown in Fig. 3. In Fig. 3 (a), predicts the actual usage of electricity before training the neural networks, therefore without neural network training it producing a huge deviation from the actual output i.e. the generation and prediction does not matches at any point. Fig. 3 (b) illustrates the prediction of actual usage of electricity and the photovoltaic generation after training in neural networks. On successful training by the Neural network, we obtain an accurate expected output.

C. Winter Day PV Generation Forecasting

An average winter day solar generation forecasting and actual consumption is shown in Fig.

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4. The illustration shows that the difference between the solar generation forecasting and actual consumption before and after the training of neural networks. Fig. 4 (a) predicts the actual consumption and generation during a winter day before training the neural networks. It is obvious that the prediction is not expected as the generation and it is also over fitting with each other. Fig. 4 (b) shows the same graphical representation after training the neural networks. It is noticeable that after neural network training there is gradual changes in the prediction and curve closely fits to generation. Thus, the employed feed forward neural network produces the solar generation prediction with high accuracy.

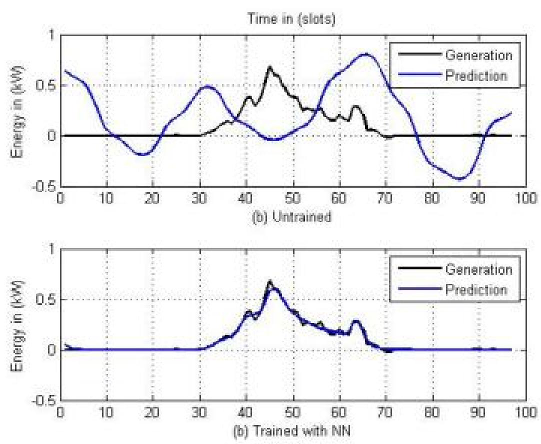

Fig. 4. Winter Day Generation Forecasting

IV. Conclusion

The short term PV generation forecasting with feed forward neural network is used to predict the solar energy generation pattern for the residential home. Moreover, the employed neural network model forecasts the photovoltaic generation pattern with high accuracy. In certain scenarios, it is little deviated from the actual generation in the peaks. This model is mostly useful for small scale power generation stations, trading of electrical energy, automatic control, storage (battery) control and real time scheduling of residential homes. It also helps to analyse the consumer energy need under control. Further, the proper prediction with storage management brings consumers benefit.

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