Short-term Forecasting for Integrated Load and Renewable Energy in Micro-grid Power Supply

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***Abstract*—: For planning and operation activities, accurate forecasting of demand is very important in sustaining the load demand in the electrical power system. Recently there has been increased use of renewable energy and unlike other sources of electricity like diesel generators, estimation of power production from renewable sources is uncertain. Therefore, reliable techniques for forecasting renewable energy and load demand are of paramount importance. Several forecasting techniques have been researched on in the past and are classified into; physical, statistical and AI techniques The proposed research involves forecasting integrated load and renewable energy (solar and wind) using Artificial Neural Network(ANN) and Enhanced Particle Swamp Optimization (EPSO) techniques. The output of this research is the predicted netload. The analysis of the results depicts ANN_EPSO as a reliable method for forecasting renewable energy and Load demand.**

***Index Terms*-- Artificial Neural Network, Enhanced Particle Swamp Optimization, Load Forecasting, Renewable Energy Forecasting.**

I. INTRODUCTION

It is impossible to ignore the fact that renewable energy, recently, has substantially been introduced into the power system. Renewable energy has proved to be cost-effective and eco-friendly compared to other sources of energy. Despite the advantages of renewable energy, there have been a challenge in predicting power generation from solar and wind due to their intermittent nature. This is a subject of interest in research since the correct forecasting for renewable energy is imperative for planning and operation purposes [5].

Forecasting is the prediction of the future happening based on present and past trends of various inputs. There are three types of forecasting based on the period of prediction; short term forecasting (STF) which has estimation period of minutes, hours to a day, mid-term foresting (MLF) has estimation period of several days, week to a month and long term foresting (LTF) has estimation period of months to several years[2]. In this paper, short term forecasting for renewable energy and load will be discussed.

Forecasting for load and renewable energy is important for planning and operation purposes in the power system, especially for generation allocation and unit dispatch for generators, marketing, and security system analysis [1].

The load demand is usually non-linear and renewable energy is usually intermittent and stochastic which makes the traditional method of forecasting less accurate and ineffective. Recently the Artificial intelligence and hybridized methods (optimization of AI and optimization techniques) have been used [3].

There has not been much attention given to the optimal net load forecasting for microgrid power systems that are highly infiltrated with renewable energy or that have a renewable energy source as the main supply of power.

The aim of this work is to provide an improved forecasting methodology for a hybrid system that integrates load demand, wind power, and solar power forecast. The main objective is to model integrated renewable energy (Wind and Solar power) and Load demand forecasting for the microgrid. Here, wind power, solar power, and load demand forecasting are done separately before integration using ANN-PSO. The results from the three models are used as input for the Netload forecasting model.

This paper is structured into four sections: Section 1 introduces the topic of research by giving a background of load and renewable energy forecasting. In section 2, a review of literature on previous similar research work is discussed. Section 3 covers the problem formulation for three forecasting models (Load, Solar, and Wind) and the formulation for Netload. The methodology is discussed in section 4, results and analysis are provided in section 5 and finally, the conclusion of the research is done in section 6.

II. LITERATURE REVIEW

Several pieces of research have been done on either load, solar, or wind forecasting separately using different methods. Each system and forecasting technique seeks to get closer to the actual values and to reduce the error between the forecasted values and the actual values. An overview of techniques used for forecasting load, wind, and solar have been discussed in [1], [9]. Separate models for forecasting

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load, power generation from solar and wind using Artificial Neural Network Feedforward backpropagation have been discussed in [2]. In [5] the researchers developed a model that forecasts the net load using outputs from solar power forecasting and Load demand forecasting. Support Vector Machine and Autoregressive methods are used respectively. A combined forecasting model that incorporates load, wind power, and solar PV power using Support vector regression Method (SVR) and GA optimization has been presented in [6]. The historical data for load demand data, wind power, and solar power is added by considering wind and solar power as negative loads.

III. PROBLEM FORMULATION

We assume that the only renewable energy generators incorporated into the grid are solar and wind. Weather parameters such as the speed of wind and temperature are used to forecast wind power generation, besides; solar irradiance and humidity have been used to forecast solar power generation.

A. Wind power forecasting

The power output from wind is given by [15]:

$$Pw = \frac{1}{2} A\rho V^3 C_P \tag{1}$$

Where Pw is the ideal power harnessed by the rotor (W), A is swept area by the rotor (m^2), V is the velocity of wind (m/s) and C_p is the power coefficient.

Accounting for the variance in the increasing speed with height, the wind velocity V at turbine height h is given by [12]:

$$V = v_o \left(\frac{\mathrm{h}}{\mathrm{h_o}}\right)^{\alpha} \tag{2}$$

Where v_o is the reference wind speed at height h_o, α implies to the friction coefficient based on the ground surface (rough or smooth terrain). Therefore, the effect of land terrain is taken into consideration in the wind power forecast.

To determine the output of wind characteristics, we use the fitting equation illustrated by a sigmoid curve as:

$$Pw(v) = \begin{cases} 0 & 0 \le V \le V_{ci} \\ A + \frac{B-A}{1+exp\left[\frac{(C-V)}{D}\right]} & V_{ci} < V < V_{co} \\ 0 & V_{co} < V \end{cases} \tag{3}$$

Where $Pw(v)$is the wind power output for a speed V, v_{ci} is the cut-in speed, v_{co} the cut-out speed (cut-in and cut-out speeds are useful in addressing uncertainties in that we know the productive speeds of wind which lead to power generation). A, B denote asymptotes acting horizontally, C is the point of inflection on the curve and D represents the scale parameter.

A 24hr future wind forecasting is employed through the ANN approach. Statistical features will be used as inputs to the ANN-EPSO model by considering the cluster approach for the network output [16], [17]. The input vector *I* is given as a function of $W_{avg,}, T_{avg}, W_{dir}, yd$ as:

$$I = [\, W_{avg,}, T_{avg}, W_{dir}, yd \,] \tag{4}$$

Where W_{avg} the average velocity of wind for the past 24hrs, T_{avg} denotes the mean temperature for the past 24 h, W_{dir} represents the direction of wind for the last 24hrs and yd denotes the specific day of the year [16].

The parameters $T_{avg}, W_{dir}, and\, yd$ are used to reduce uncertainty and improve accuracy. ANN model output gives the expected production of power for 24hrs ahead.

B. Solar Power Forecasting

The power output for a PV module is given by [9], [10];

$$P_s = I_T\alpha\{1 - \gamma(T_{cell} - T_{ref})\} \tag{5}$$

Where I_T is the solar incident radiation, α is a constant which is the product of the packing factor and efficiency module estimated to be about 0.11, T_{ref} is the reference temperature set at 25℃ and γ is the temperature coefficient set at -0.47%. The operating temperature T_{cell} is given by [10]:

$$T_{cell} = T_{air} + (0.0125NOCT -)0.25)S \tag{6}$$

Where *NOCT* is taken to be 50℃, T_{air} is the real-time data on the ambient air temperature and *S* is the insolation level valued at 80 mW/cm^2.

$$I = [I_T, T_{air}] \tag{7}$$

$\mathrm{I_T}$ and T_{air} will be the input variables *I* for the artificial neural network.

C. Forecasting the load demand

The load demand will also be predicted using ANN. EPSO algorithm will replace the inbuilt backpropagation algorithm for the training method in the ANN structure. This would help reduce the forecasting error of the ANN [11].

For accurate forecasting, the days of the week will be divided up as Monday type, Weekday type, Saturday type, and Sunday type. The input to the ANN will be as follows in equation 8;

$$L = [\, P_h, T_h \,, X_s,] \tag{8}$$

Where $\mathrm{P_h}$ the historical is hourly load demand, T_h is the daily average temperature and X_s is the type of day. Type of day is divided up as Sunday, Saturday, and Weekday types.

Load data will be taken on an hourly basis, temperature on an hourly basis, and season input as a number from one to four.

The output will be the forecasted load for 24hrs ahead.

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D. Net forecasted Load

To achieve the forecasted netload, the results from forecasted wind power, solar power generation and forecasted load demand are used as inputs. The forecasted power from the wind turbines and PV solar generators are treated as negative loads. The difference between the forecasted load demand and the forecasted power produced from renewable energy generators is considered the forecasted net load demand. The forecasted net load $NL(t)$ is important for the management of the total hourly energy balance.

$$NL(t) = Pd(t) - (P_w(t) + P_s(t)) \tag{9}$$

Where $Pd(t)$power is the forecasted load and $P_w(t)$ is the total forecasted power production by wind turbines and $P_S\,(t)$ is the forecasted solar power. If $NL(t) < 0$, there is an excess production compared to demand. Surplus energy is thus sold to the grid or managed by the energy management system. If $NL(t) > 0$, the load demand exceeds production and the difference is bought from the grid (this ensures there is no loss of power supply).

Total power required to be generated will be given by:

$$\sum_{i=1}^{N} Pw + P_S + \sum_{i}^{N} P_{grid} \geq P_D + P_{loss} \tag{10}$$

Where P_D is the forecasted total load power demand, P_{grid} is the total power supply from established traditional methods for example (hydropower) and P_{loss} is the transmission power losses.

Figure 1 represents the forecasting model for solar power, wind power, and load. The outputs are then used as inputs for the net load forecasting.

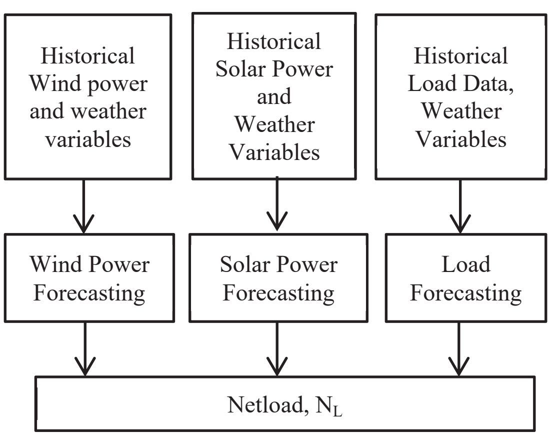

Figure 1: Proposed forecasting Model

IV. METHODOLOGY: ARTIFICIAL NEURAL NETWORKS (ANN) AND ENHANCED PARTICLE SWARM OPTIMIZATION (EPSO)

A. Artificial Neural Network (ANN)

ANNs are models that were developed based on the structure of the brain, inspired by the idea that the brain learns by experience. They are characterized by a parallel architecture comprising of neurons and a large degree of feedback [22]. The ANNs is comprised of numerous nodes and neuron that interconnect and interrelate with each other. Each node's output is called its activation or node value. Artificial Neural Network can learn weights and change their values.

B. Enhanced Particle Swarm Optimization

Particle swarm optimization is analogies of the birds going randomly to hunt for food; the birds nearest to the found food leave a hint or signal to attract the flock behind to the found food. [19]. If any other birds come closer to the target than the first, then they also give a signal until one of the birds in the flock stumbles upon the found the recursion of this reduction pattern continues.

Over several repetitions, a group of birds has their values adjusted closer to the member whose value is closest to the food at any given moment. This process is repeated until the best conditions or a food source is discovered. The process of optimization follows the work of these birds' behavior. The solution coordinates indicators and the speed of the particles as the optimal solution is approached is given by the velocity and the particle position. [21]. Birds are mapped as particles whereas signals as positions and velocities and finally foods being the solutions.

EPSO is used to optimize the ANN parameters.

Presentation of EPSO

The position and velocity of each particle are updated per iteration as follows:

$$V_{i,iter+1} = \omega V_{i,iter} + C_{1b} r_1 \left(P_{i,iter}^{b} - X_{i,iter}\right) + C_{1nb} r_2 \left(X_{i,iter} - P_{i,iter}^{not_b}\right) + C_2 r_3 \tag{11}$$

$$X_{i,iter+1} = \left(X_{i,iter} + V_{i,iter+1}\right) \tag{12}$$

The coefficients C_{1b} and C_{1nb} are related to the 'b' and 'not-bt' components.

C. Data preparation

The datasets used for load, solar, wind forecasting is obtained from Global Energy Forecast, GEFCOM2014. The dataset is covers a period of one month and is classified into hourly historical data and hourly records of weather variables for the respective forecasting models. It is assumed that data is obtain from the same region and that both solar PV and wind turbine generators are serving the same micro-grid

The input dataset is standardized to minimize the probability of getting stuck in local minima and local optima. It also helps in increasing the speed of training data.

The weather variables are normalized between a value of (-1 to +1) using min-max normalization.

$$Y_j = \frac{X_j - \mathrm{Min}(x)}{\mathrm{Max}(x)} \tag{13}$$

D. ANN-EPSO Forecasting Model

The ANN-EPSO model discussed in this paper is used to forecast wind power, solar power generation, load demand and the net load for the next 24hrs.

For modeling ANN_EPSO, Matlab 2018a is used. The Structure for ANN is developed as shown in figure 2. The network is created by defining and configuring the number of inputs, hidden layers, the number of neurons in each layer,

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and the number of output. The activation function, biases and weights are defined and initialized. The Network is then trained using EPSO. EPSO optimizes the network by giving the optimum values for biases and weights of the ANN network. The output from each model; Load, wind power, and solar power forecasting model are used as input for the net load forecasting model.

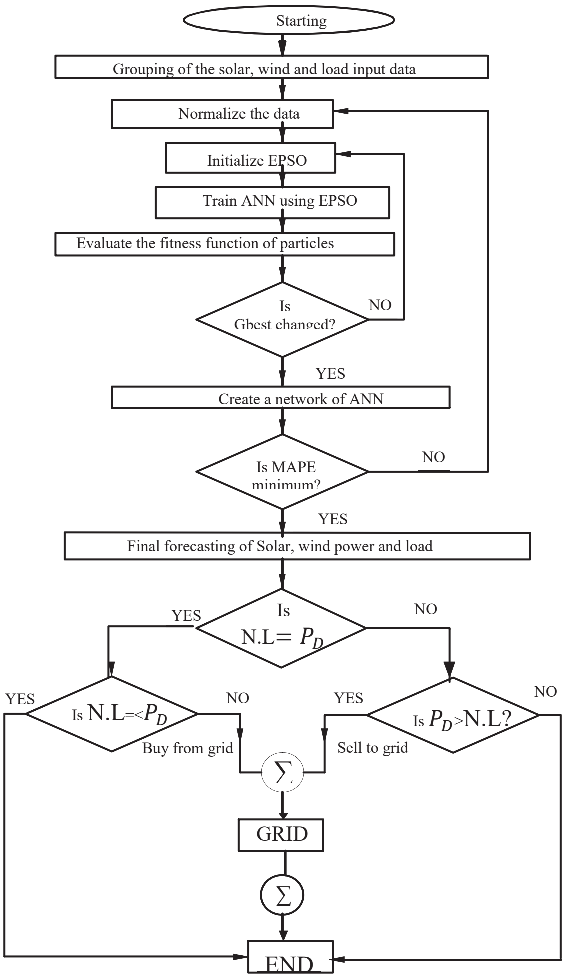

Figure 2: Flow-chart for Load, Wind and Solar forecasting using ANN- EPSO

V. RESULTS AND ANALYSIS

Figure 3-5 shows the graphs representing the simulated results, which depicts that the forecasting models are effective in predicting Load demand, wind power, and solar power generation since the curves of the predicted values are almost similar to one of the actual values.

The reliability of the model is determined from the Mean Absolute Percentage Error (MAPE), as in equation 14 [1]:

$$MAPE = \frac{1}{N}\sum_{j=1}^{N}\frac{\left|P_a^j - P_f^j\right|}{P_a^j} \times 100 \qquad (14)$$

Where; N denotes the number of cases forecasted, P_a^j the actual power, and P_f^j the amount of forecasted power.

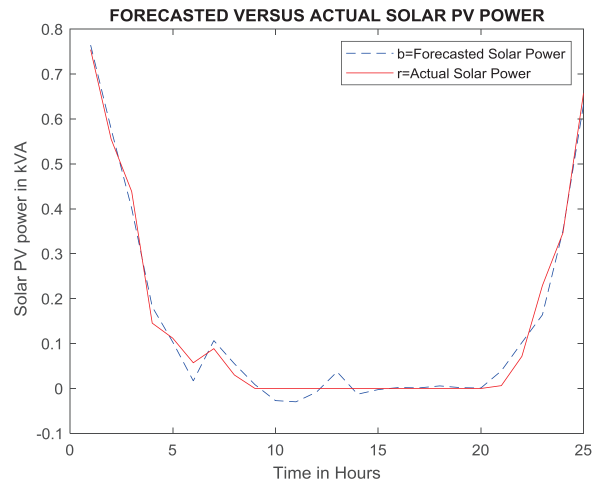

Figure 3: Forecasted Solar power

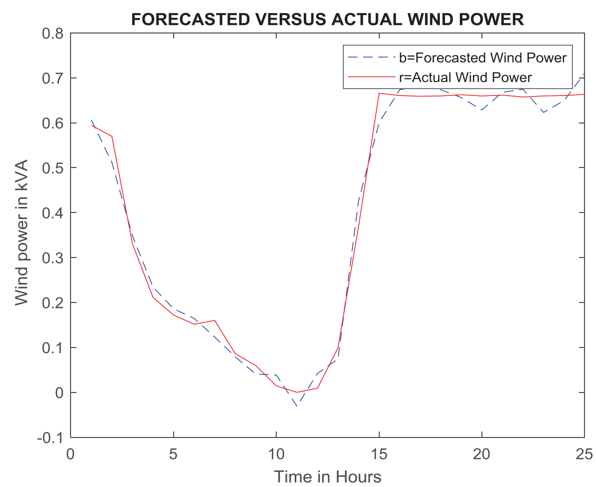

Figure 4: Forecasted Wind power

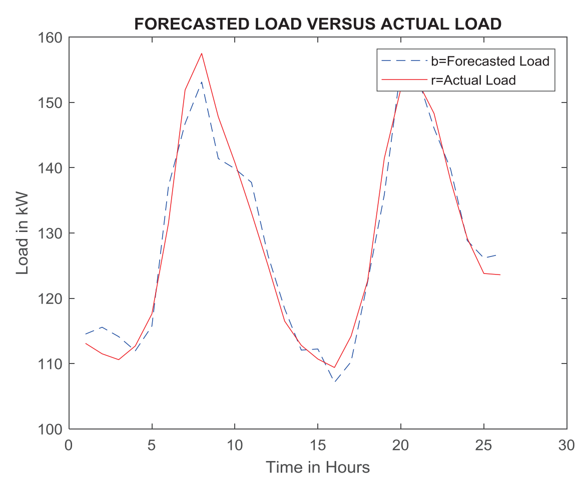

Figure 5: Forecasted Load demand

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Table I: Mean Absolute percentage Error for the forecasting model

Forecasting Model	MAPE
Load demand forecasting	1.370%
Solar power forecasting	0.126%
Wind power forecasting	0.268%

The results indicate that the error from the actual values is small for the three forecasting models.

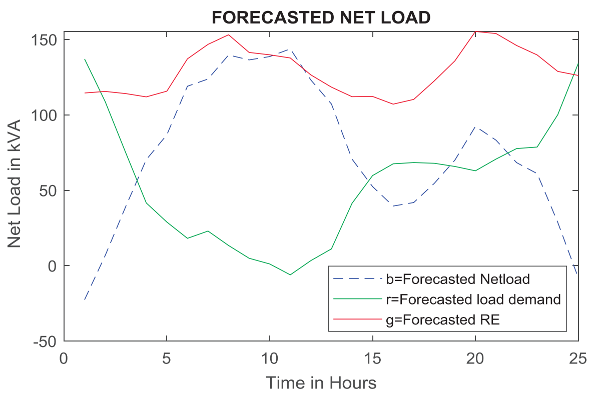

Figure 6: Forecasted Netload

Figure 6 represents the forecasted net load compared to the forecasted load demand and the total forecasted renewable energy. Negative net load means that the forecasted renewable energy is less than the forecasted load demand and therefore requires additional power from either the grid or other sources of power supply to meet the load demand. A positive net load means that the forecasted renewable energy generation is more than the forecasted load demand; the excess power is either stored or sold to the grid

VI. CONCLUSION AND RECOMMENDATION

Electric power grids and isolated power systems with high infiltration of renewable energy sources are highly faced with the challenge of predicting the expected amount of power generation from renewable generators. This is due to the intermittent nature of weather variables that affect power generation. In this research load demand, solar power and wind power generation are forecasted on separate models on hourly basis. The results from the three models integrated to predict the hourly net load for the power system. This model is applicable in any microgrid power system that has a high penetration of renewable energy. Based on the error indicators, the hybrid model using ANN-EPSO gives an improved performance compare to ANN model used in [2] and Support Vector machine model used in [6]. Further research can be done to explore the possibility of a real-time forecasting system that updates data online for renewable energy production and load demand.

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