Dynamic Performance Model of Wind Turbine Generators

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Abstract—**To characterize the power performance of wind turbine generators (WTGs), the International Electrotechnical Commission provides a power curve for each one based on ten minutes average. This approach causes the problem of systematic errors because of the nonlinear relationship between power and wind speed. In this paper, recurrent neural networks are introduced as an alternative approach to model this nonlinear relationship. Based on actual wind speed input and wind power output, an input-output relationship is established for a permanent magnet synchronous machine based wind power generator. Experimental studies are carried out to the develop power curve that characterize dynamic power performance of the wind turbine generator. These dynamic power performance models of wind turbine generators can be used as operational and planning models in control centers. Some preliminary results on the integration of a neural network wind generator model in a micro-grid simulation is presented.**

Keywords—dynamic neural network; dynamic performance model; micro-grid; power estimation; wind turbine; particle swarm optimization

I. INTRODUCTION

Modeling of wind turbine is always a challenge due to unpredictable and complex wind dynamics such as continuously varying wind speed and wind direction. The electrical power output from a wind turbine generator is driven by the wind dynamics, so it is imperative to study the relation between wind speed and output power in the form of power curve of the machine. Wind turbine manufacturers publish and certify power curves for turbines based on the industry standard IEC 61400-12-1 which is based on ten minutes average. These wind turbine power curves are used for planning purposes and estimating total wind power production. When a wind plant consisting of many wind turbines connects to the utility grid and starts operation, the focus shifts to the entire plant's performance. An equivalent wind plant power-curve becomes highly desirable and useful in predicting plant output for a given wind forecast [1, 2].

Traditional methods of wind turbine modeling and prediction are usually based on turbine's power curve or based on the simulation of wind power generators [3] or statistical method such as auto-regression [4,5]. These, however, are not able to explain varying characteristics in wind dynamics. According to IEC Standard 61400-12-1 (power performance measurements of electricity producing wind turbine), wind velocity are collected and averaged over 10-minute periods which does not properly quantify energy content of the wind but underestimates by significant amounts when there is a large variation in the wind speed. There are multiple power productions points for the same wind speed. This approach causes problem of systematic errors because of the nonlinear relationship between power and wind speed. The power output not only depends on present wind speed but also depends on previous time step inputs. When input and output parameters such as wind speed and wind directions, and wind power, respectively are known for an installed wind turbine generation plant, computational approaches such as a neural network model can be used to develop a dynamic operation model and estimate wind power generation with less errors.

Feed-forward neural networks with supervised back propagation training algorithm have been used to estimate wind turbine power generation [6] and to develop nonlinear model of wind turbine [7]. Comparison of regression and neural network models for the estimation of wind turbine power curves were carried out and better results have been reported with neural networks [8]. Elman recurrent neural network (RNN), a dynamic neural network, provides better accuracy than a static feed-forward neural network [9, 10] and has the ability to adapt to time-varying patterns. Therefore, this is more suitable among the neural networks for dynamic performance modeling wind turbine generators based on actual wind plant data.

The study carried out in this paper presents the development of a dynamic performance model of a single wind turbine, a dynamic power curve. The predicted power output of the turbine is independent of turbine operations and control schemes but only based on wind speed. Measurements of power output and wind speed are made at low frequency to develop a dynamic power curve. A dynamic neural network, Elman RNN, is used for the power curve characterization. The RNN coefficients (weights) are learned using particle swarm optimization (PSO). The dynamic wind generator performance is integrated in a micro-grid simulation to replace a wind generator model, and typical results are shown that such as model can be used in short-term planning studies.

The reminder of the paper is organized as follows. Section II describes the development of dynamic wind turbine model using Elman RNN and improved PSO algorithms. Section III describes Skystream 3.7 wind turbine used in the experimental study. RNN development and results are presented in Sections IV and V, respectively. Section VI illustrates an application of dynamic performance model based wind turbine for real-time simulation of a micro-grid. Finally, the conclusion is given in Section VII.

II.   DYNAMIC PERFORMANCE MODEL

Wind turbine output power is dependent on the dynamics of wind speed, direction, wind turbine type, generator type, power converter, and their associated controls as shown in Fig. 1. Wind turbine rotor dynamics is represented by (1) which is a relationship between wind speed and mechanical power produced [11].

$$P_m = 0.5 \cdot C_p(\lambda, \beta) \cdot \rho \cdot A \cdot u^3 \qquad (1)$$

where,

P_m is mechanical power output of wind turbine in Watts
ρ is air density in kg/m^3
A is swept area of turbine blades in m^2
u is wind velocity in m/s
$C_p(\lambda, \beta)$ is the power coefficient of wind turbine and a function of tip speed ratio (λ) and blade pitch angle (β)

The power coefficient is a measure of efficiency of the wind turbine in converting wind energy into mechanical energy and is generally less than 0.5. Power coefficient equations found in literature [11, 12] are highly non-linear due to various aerodynamics factors such as blade pitch angle, angle of attach, wind speed, tip speed ratio, number of blades, turbine radius. Wind turbine is designed to stop turning for exceeding cut-off speed and start rotation after meeting cut-in speed. These effects are dependent on power coefficient curve which is a function of tip speed ratio and blade pitch angle.

Wind turbines are classified based on mechanical power control such as pitch control or stall regulation; fixed speed, variable speed and full power electronic conversion based on speed control. Modeling of wind turbine is thus a challenge due to complex function approximations between wind speed, wind direction and associated turbine-generator dynamics and controls. Neural networks (NNs) comprise one of the computational intelligence paradigms and are used to represent the dynamics of the system by training on the behavior of the system over time without any knowledge of actual structures. Multi-layer perceptron (MLP) network has a feedforward architecture, and is the simplest one with three layers. Input, hidden and output layers comprising a number of neurons forms the MLP network. RNN has a feedback architecture, however is similar to MLP architecture except it contains a feedback loop with unit delay from a subsequent layer of a network back to the input layer. Elman network is a form of RNN where feedback from hidden layer is fed back as a context which allows the network to learn to recognize and generate temporal patterns. Structure of an Elman RNN is shown in Fig. 2.
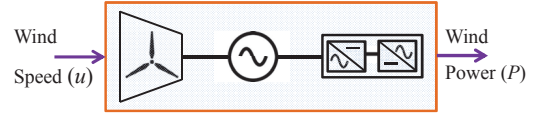

Fig. 1. Typical dynamic components of wind turbine generator
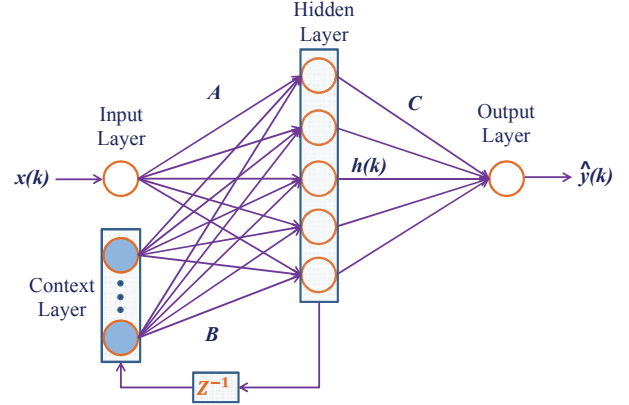

Fig. 2. Elman recurrent neural network architecture

Elman network is chosen in this study to allow feedback of the hidden states to context layer as input. A comparison of feedforward and feedback neural network architectures for wind speed prediction is presented in [13]. In the study, activation functions in input, context and output layers are linear while activation functions in hidden layer are sigmoids. Estimated output $\hat{y}(k)$ using Elman RNN is given by (2)

$$\hat{y}(k) = C \cdot sigmoid\ (A \cdot x(k) + B \cdot h(k-1)) \qquad (2)$$

where,

$h(k-1) = sigmoid\ (A \cdot x(k) + B \cdot h(k-2))$
h = hidden layer output states
x = input to the Elman RNN
A = weight matrix between inputs and hidden layer
B = weight matrix between context and hidden layer
C = weight matrix between hidden and output layer.

Particle swarm optimization is based on the principle of swarm behavior of birds introduced by Kennedy and Eberhart [14]. The system initially has a population of random solutions called particles. Each particle has random velocity and memory that keeps track of previous best position and corresponding fitness. Previous best value of the particle position is called the '*Pbest*' and '*Gbest*' is the best value of all '*Pbest*' positions in the swarm. Basic concept of PSO lies in accelerating each particle towards its *Pbest* and the *Gbest* locations at each time step. The application of PSO algorithm is based on the minimization of error in the output. Particles' positions are defined as weights A, B and C of the neural network. Weights are updated every time until minimum fitness is achieved. Position and velocity of each particle is updated according to (3) and (4) respectively. The fitness value is calculated in (5).

$$V_{idnew} = w \cdot V_{id} + c_1 \cdot rand_1 \cdot (Pbest_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (Gbest_{id} - X_{id}) \quad (3)$$

$$X_{idnew} = X_{id} + V_{idnew} \quad (4)$$

$$Fitness = \frac{1}{n}\sum_{j=1}^{n}(y(k) - \hat{y}(k))^2 \quad (5)$$

where,

i = no. of particles in the PSO algorithm
d = dimension of each particle
w = inertia weight
c_1, and c_2 = cognitive and social acceleration constants
$rand_1$, $rand_2$ = random numbers
X_{id} = current particle position
V_{id} = current particle velocity
X_{idnew} = next particle position
V_{idnew} = next particle velocity
$Pbest_{id}$ = best solution of the particle
$Gbest_{id}$ = best solution of whole population
n = number of data points used to map the input-output
$y(k)$ = actual wind power output of the wind generator
$\hat{y}(k)$ = estimated power output of the wind generator.

The manufacturer's power curve is a static model presenting relationship between input speed and output power. Dynamic performance characterization and modeling of a grid-connected wind turbine generator is developed using Elman RNN as shown in Fig. 3, where $W_S(t)$ is the actual input wind speed and $W_P(t)$ is the actual wind power, and is used as the target for training the RNN. RNN uses simultaneously sampled wind speed and wind output power data over a period of time to learn input/output relationship and estimate output power $\widehat{W}_P(t)$. Wind speed and time delayed feedback from hidden layer is used as RNN inputs. Thus, estimated power output is not only function of present wind speed but also dependent on previous dynamics. Neural network weights are updated over iterations until a pre-specified fitness is achieved initially and thereafter maintained during real-time operation.

III. EXPERIMENTAL STUDY WITH SKYSTREAM 3.7

A single-phase permanent magnet synchronous machine (PMSM) type 2.4 kW wind turbine (Skystream 3.7) is used for the dynamic performance modeling. The turbine parameters, generator electro-mechanical parameters and associated controls required for dynamic studies of Skystream 3.7 is not easily available from the manufacturer. Thus, the wind turbine is modeled using an Elman RNN with wind speed and wind power data as input information. As per manufacturer catalogue, Skystream 3.7 is designed for rated wind speed of 13 m/s and cut in wind speed of 3.5 m/s.
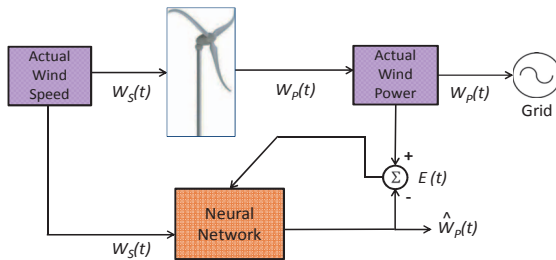

Fig.3. Dynamic modeling of wind turbine using Elman RNN

Wind speed and wind power data are collected for Skystream 3.7 using Skyview software at one second resolution. In order to represent winter and summer wind profiles, wind speed and wind power data collected on 18-19 November, 2011 (winter) for 34 hours 14 minutes are used as training data while wind speed and wind power data collected on 6 April, 2011 for 1 hour 54 minutes are used as testing data. In this paper, the winter results are only presented. The maximum wind speed recorded is 23m/s and the maximum output from Skystream 3.7 is 3.6 kW. Fig. 4 shows the relationship between measured wind power and wind speed, which is also the power curve, for the Skystream 3.7 used. The power curve for the Skystream 3.7 wind turbine obtained from manufacturer is shown in Fig. 5 [15]. Comparing these two figures, it is clearly observed that manufacturer's curve is not capable of capturing the wind turbine dynamics correctly.
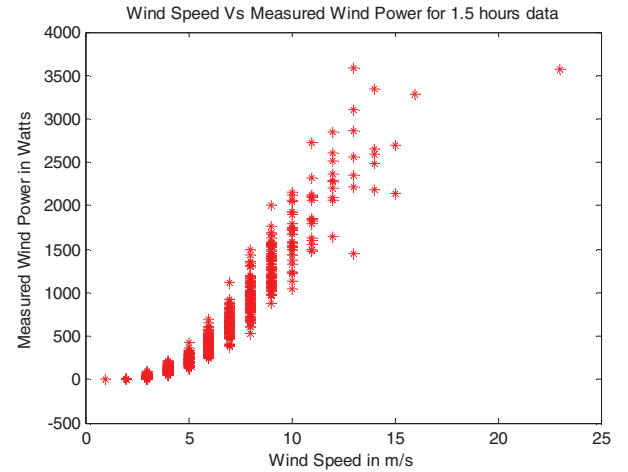

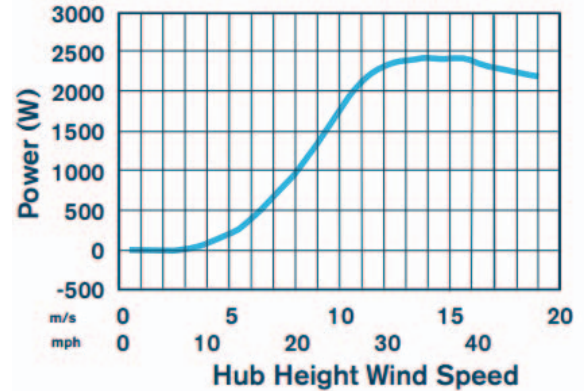Fig. 4. Measured power curve using Skystream 3.7 wind turbine

Fig. 5. Manufacturer power curve for Skystream 3.7 wind turbine [15]

IV. RNN DEVELOPMENT

The Elman RNN used in this study consists of an input layer with single neuron, a hidden layer with five neurons and an output layer with a single neuron. The context layer has five neurons, same as the hidden layer. The input, context and output layers have linear activation functions while activation functions in the hidden layer are sigmoids. The wind speed, wind power are the input and output of the Elman RNN,

respectively. All the wind speed data and wind power data are normalized to the interval [0 to 1]. Time delayed feedback from hidden layer to context layer stores the temporal properties of wind turbine generator system. Thus *A*, *B*, *C* weight matrices have a size of 1×5, 5×5 and 5×1. The total number of weights is 35. The choice of number of neurons in the hidden layer is selected by trial and error. Best results were observed with hidden neurons between 4 and 10. The scope of this paper is not to obtain the optimal architecture of the neural network. Therefore, it is not claimed to be optimal. There are several methods in literature to find the optimal network structure and size.

The parameters of PSO algorithm are chosen based on previous work [16]. PSO with 35 particles is implemented to learn the weights of Elman RNN. The inertia term is reduced from 0.8 to 0.4 over 5000 iterations, and the cognitive and social acceleration constants are chosen as 2. A search space range of (-10, 10), and maximum/minimum velocity of 0.2/-0.2 are used in the study. Every 100 iterations, all the particles except the global best are replaced with regenerated particles to avoid chance of getting trapped in local minima [17]. Target fitness was set to 1×10^{-3} and training iterations were restricted to 5000 to avoid overtraining. Final weights of the Elman RNN are used for testing Skystream 3.7 dynamic performance.

V. RESULTS

Mean square error (MSE) of the global best particle improves over iterations of training the Elman RNN as shown in Fig. 6. Figs. 7 and 8 illustrate testing plot of wind power estimation of the Skystream 3.7 where output power closely follows the target power. Normalized mean square error is found as 1.3×10^{-3} and 8.3×10^{-4} for 1.5 hour and 20 minutes test data sets, respectively which illustrates successful learning of wind turbine's power curve.

Table I presents mean absolute relative error (ARE) of testing data set for two different time periods. It is found that about 7.2% of testing data sets have ARE greater than 200%. Mean ARE for the testing set for 1.5 hours and 20 minutes are calculated as 22.5% and 27.39%. Fig. 9 shows relationship between estimated wind power generation in Watts and wind speed in m/s for a Skystream 3.7 wind turbine obtained using Elman RNN for 1.5 hours of test data. This is observed to very close to measured power curve. Thus, RNNs can be implemented as an intelligent technique for learning wind turbine generator power dynamics (power curve).

TABLE I

MEAN ABSOLUTE RELATIVE ERROR FOR SKYSTREM 3.7 WT

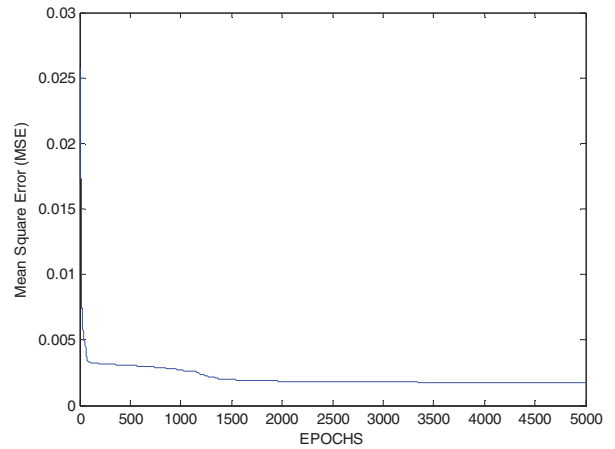|	Percentage of data with less than 200% ARE	Mean ARE in Percentage
Testing Set (1.5 hours)	93.3	22.5
Testing Set (20 minutes)	91.96	27.36

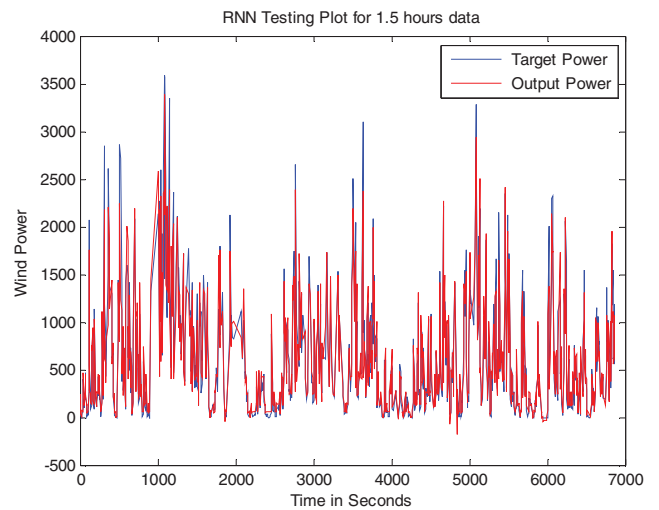Fig. 6. Fitness of the *Gbest* particle over time during training

Fig. 7. Estimated Power in Watts of Skystream 3.7 for 1.5 hours data
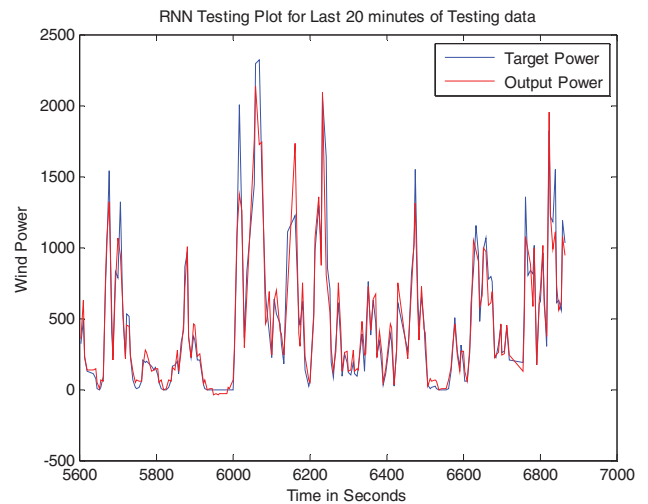

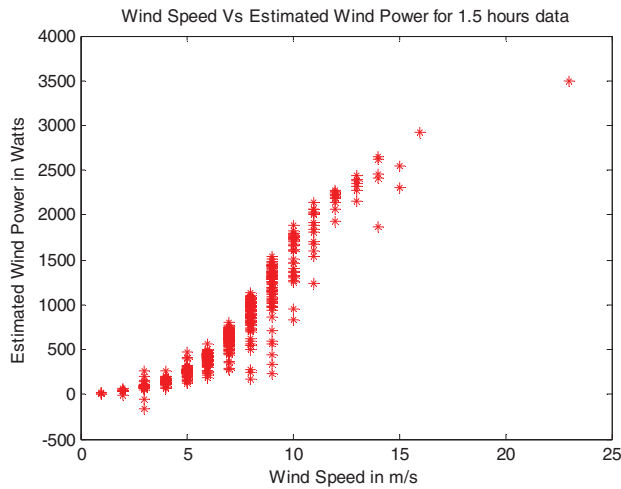Fig. 8. Estimated Power in Watts of Skystream 3.7 for 20 min data

Fig. 9. Estimated power curve for Skystream 3.7 using Elman RNN

VI. APPLICATION OF DYNAMIC PERFORMANCE MODEL BASED WIND TURBINE IN A MICRO-GRID SIMULATION

The dynamic performance model of wind turbine generator is integrated into a real-time simulation model of micro-grid with unbalanced sources. The 208 VAC, 60 Hz micro-grid structure in the study consists of energy storage system (a battery inverter system), 4.8 kW three-phase solar photovoltaic with irradiance and temperature as input parameter, a 2.4 kW single-phase wind generation represented by dynamic performance model based wind turbine with wind speed as input and 6 kW fixed load which represents both critical and controllable load as illustrated in Fig. 10. Energy storage system with negative sequence current control has been realized for regulation of the micro-grid voltage, frequency and compensation of the various source types [18].
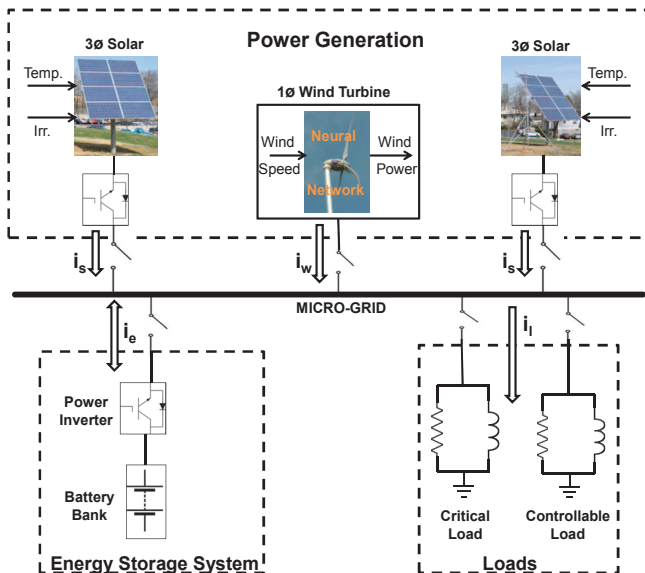

Fig. 10. Generic model of a micro-grid system.

Variation of wind speed and estimated output wind power for Skystream 3.7 over 100 seconds with resolution of one second is shown in Fig. 11. A single phase wind generator (Skystream 3.7) is developed by estimating wind power output based on input wind speed information using the RNN model developed above. Output wind power is then converted into voltage magnitude and phase angle and fed into the single phase controllable voltage source.

The energy sources, solar and wind, supply active power required by micro-grid while energy storage supplies unmet active and reactive power. Fig. 12 shows the active and reactive power flow from solar and battery to meet the 7.5 kVA load with lagging 0.8 pf. Fig. 13 illustrates active and reactive power after integration of 2.4 kW wind turbine generator into the micro-grid. Since the wind power generation changes every second; the energy storage device is capable to absorb excess energy or supply unmet energy.
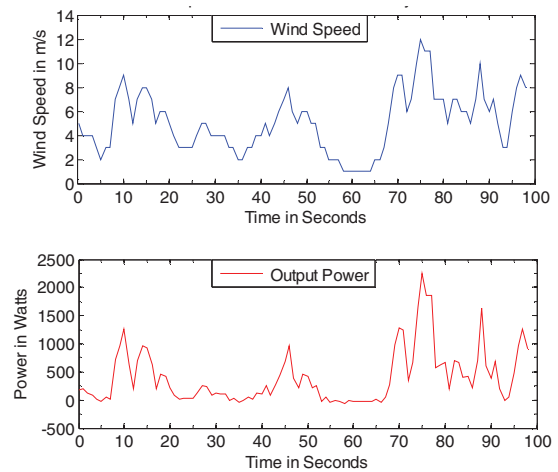

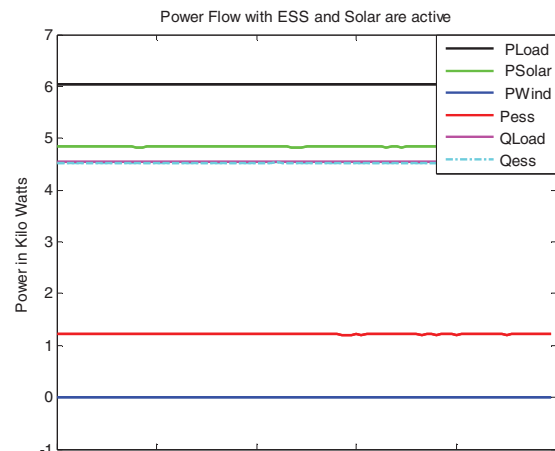Fig. 11. Wind speed & estimated output power variations for every second

Fig. 12. Active and reactive power flow when solar and energy storage are active to supply 7.5 kVA load

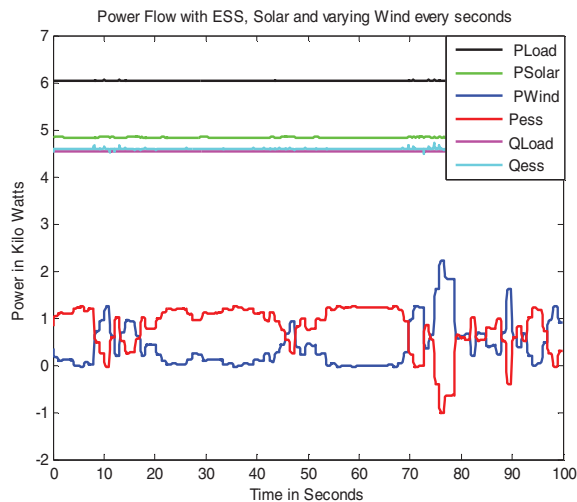Power Flow with ESS, Solar and varying Wind every seconds

Fig. 13. Active and reactive power flow when solar, energy storage, and wind are active to supply 7.5 kVA load

VII. CONCLUSION

Dynamic performance model of a wind turbine is an essential tool for control room operators predicting wind turbine power output for a given wind speed forecast. For a wind farm consisting of hundreds and thousands of turbines connected to the utility, entire farm performance has to be modeled based on the individual wind turbine complex dynamic models. Such a model will account for the changes in wind direction, wind speed, local topography and type of wind turbine layout.

At a particular wind speed, wind turbine can generate a range of wind power contradicting to manufacturer's power curve; thus traditional methods of wind power estimation are not able to produce actual wind turbine power dynamics. However, recurrent neural networks are used to learn overall wind turbine characteristics and estimate the wind power. The dynamic performance model of a 2.4 kW Skystream 3.7 has been considered in the study for wind power estimation. To demonstrate the application of wind turbine modeling, neural network based Skystream 3.7 is integrated into the real-time micro-grid simulation with solar photovoltaic, energy storage system and loads. The results conclude on the fact that irrespective of knowledge of types of wind turbine, electro-mechanical parameters and associated controls, dynamic model can be developed for power estimation.

Wind power is depended not only on wind speed but also on air density (characterized by pressure, temperature, humidity), wind direction. As a part of future work, improved model will be developed with wind direction and air density as additional inputs to the network. A dynamic equivalent wind turbine model considering sequence networks, short circuit behavior, etc. will be studied in the future.

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