IMPACT OF WIND FARM INTEGRATION ON ELECTRICITY GENERATION COST USING ANN AND PSO

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Abstract: *This paper presents an efficient approach using particle swarm optimization to solve optimal power flow problem including wind power generation. In this study, opportunistic costs of wind power surplus and shortage are taken into consideration. Artificial neural network is used to predict the wind speed where the data to train ANN were collected from Radhapuram, southern part of TamilNadu in India. The wind power cost is estimated for the predicted power of wind farm. The proposed method is tested on a modified IEEE 30 bus system by forming a virtual wind farm and integrating it to different load buses and the suitable bus for the integration of wind farm is chosen based on minimum generation cost using PSO. The simulation results demonstrate the influence of wind power variation in the overall generation cost of the system when it is integrated to a power system.*

***Key Words**:*
Artificial Neural Network (ANN), Particle Swarm Optimization (PSO), Optimal Power Flow (OPF), MATPOWER, Wind Farm integration.

1. Introduction:

The growth of renewable energy in power systems has been increasing due to increased concern over global warming. Wind resources provide a cheap and clean source of energy. Wind power, as an electricity generation source, plays a major role in immediate and longer term energy plans of large number of countries. Utility companies are increasingly relying on wind energy to meet their growing demand. The integration of wind energy to a power system grid faces tough challenges which include the power system generation cost, power quality issues, power fluctuations and impacts on transmission planning [1].

The power fluctuation plays a key role in the determination of wind power generation cost in an integrated power system. Although the cost of wind power is cheaper, it varies due to nonlinear fluctuations in the wind speed and power. The generated wind power may be either less or more compared to the scheduled power to the system. This causes variation in wind generation cost; hence it becomes more significant to optimize the scheduled wind power. Accurate prediction of wind power gains more importance in the estimation of wind power cost. Inaccurate power prediction may result either in underestimated or overestimated generation cost, which would lead to either loss to consumers or loss to wind farm owners [2]. Libao Shi et.al.[3] predicted wind speed based on Weibull wind speed distribution and Monte Carlo simulation. Artificial Intelligence techniques play key roles in the prediction of wind speed. Many studies proved that Artificial Intelligence (AI) techniques are found to be more efficient as compared to traditional statistical models for the prediction of wind power [6,7]. Different types of neural networks were used to predict the wind and power output of wind farms in [4-8]. In this paper, the wind speed prediction is based on feed forward ANN which is trained using real time wind speed data. Using the predicted speed, a virtual wind farm is framed and the cost of wind power generation is determined using the model proposed in [3].

After the determination of the wind generation cost, it is necessary to include it in the optimal power flow (OPF) to get the optimum scheduled power of the wind farm. The OPF aims at minimizing the generation cost via optimal adjustment of control parameters (Power Generation), at the same time satisfying certain equality and inequality constraints. There are many conventional methods to solve OPF that make use of derivatives and gradients [9-12]. OPF is a highly nonlinear and multimodal optimization problem; hence there exists more than one local optimum. The conventional techniques are not able to exactly locate the global optimum value. Evolutionary algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) etc. are more suitable under these circumstances [3,13,14]. However Fogel [15] has identified that the premature convergence of GA degrades its performance and reduces its search capability. The PSO has wide range of applications in power systems [16]. PSO has been effectively utilized for optimal dispatch of reactive power [17]. Hence this paper considers PSO to run OPF with wind power integration.

Section 2 of this paper explains the process flow adapted in this this work, section 3 has three parts where the first part discusses the wind prediction using ANN, second part describes the calculation of wind power generation cost and the third part explains the integration of wind farm to a IEEE 30 bus test system and analysis of results.

2. Proposed Methodology:

The process flow of the proposed work is depicted in figure 1. The flow starts with collection of real time wind speed data which is then scaled and used to train the ANN. Using ANN, the future wind speed data is predicted and using the predicted wind speed data, the output power of wind farm for the year 2016 is predetermined. The cost of the wind power is calculated using the mathematical cost model proposed by Libao Shi et.al.[3]. The cost, thus calculated for wind power is incorporated in OPF and the total generation cost is determined for modified IEEE 30 bus system by integrating wind farms to various load buses. The OPF is performed using PSO.

The detailed steps involved in this process are explained below.

a.)Wind Speed data history:

To train the ANN for the prediction of wind speed, it is necessary to have proper dataset. Selection of inputs and output plays a key role in this process. We have considered year, month, day & time (hourly) as the inputs and Wind speed as the output at same altitude and constant air density. Also this data collection requires appropriate area where wind speed history is to be collected. The details of wind speed history and its justification are discussed in the results section.

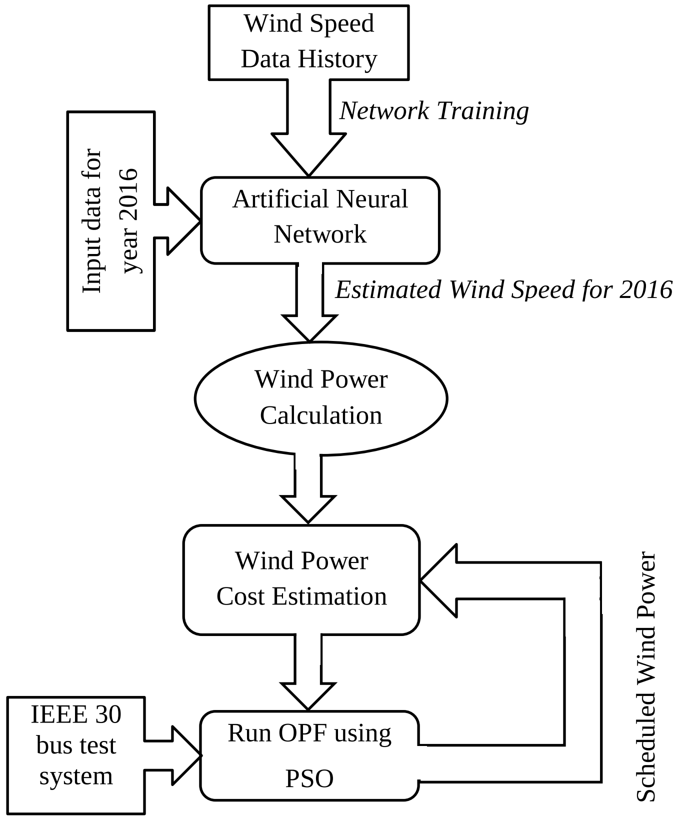

Fig.1. Process Flow Diagram

b.)Artificial Neural Networks:

ANN is an information processing system that extracts information from the data to develop complex relationship between input and output. The input variables are multiplied by connection weights and its products, biases are added and passed through transfer functions for generating output [18]. The network is decided by its architecture, activation function and training algorithm. The architecture determines connection pattern among neurons. During training, the values of connection weights and biases are updated to minimize the mean square value of output error. The extracted real time wind speed data is used to train the ANN. Once it is trained with minimum error, the network will be tested for untrained data. Once the network is tested fine, it can be used to predict the future wind speed. This architecture is given in figure 2.

c.)Optimal Power Flow

The Optimal Power Flow is an intellectual load flow that employs techniques to automatically adjust the power system control settings while simultaneously solving the load flows and optimizing operating conditions within specific constraints. The optimization problem is minimization of cost function subjected to various constraints.

The objective function is Min(C) where C is the total generation cost of the power system which is given by,

$$C = \sum_{i=1}^{N} F_i(P_i) + C_{wind}(P_{Sch}) \quad (1)$$

where $F_i(P_i)$ is the cost function for generator connected at bus 'i' which is given by $Fi=a_iP_i^2+b_iP_i+c_i$ and 'i' belongs to all generators in the system except wind generator, P_i is the power output for generator 'i' , C_{wind} is the cost of wind farm power output and P_{sch} is the scheduled wind farm output. The function, "C" is minimized subject to the following equations.

$$P_{Gi} - P_{Li} = \sum_{j=1}^{N} |V_i||V_j||Y_{ij}| \cos(\Theta_{ij} + \delta_j - \delta_i) \quad (2)$$

$$Q_{Gi} - Q_{Li} = -\sum_{j=1}^{N} |V_i||V_j||Y_{ij}| \sin(\Theta_{ij} + \delta_j - \delta_i) \quad (3)$$

$$P_i^{min} \le P_i \le P_i^{max} \quad (4)$$

$$Q_i^{min} \le Q_i \le Q_i^{max} \quad (5)$$

$$|V|_i^{min} \le |V|_i \le |V|_i^{max} \quad (6)$$

where P_{Gi} & Q_{Gi} are the real and reactive power generation at bus 'i' , P_{Li} & Q_{Li} are the real and reactive power demand at bus 'i' , V_i is the voltage at bus 'i' , Θ_{ij} is the angle corresponding to bus admittance matrix element between nodes 'i' and 'j' , δ_i is the voltage angle at bus 'i', P_i^{min} & P_i^{max} are the minimum and maximum limits of real power generation for generator 'i', Q_i^{min} & Q_i^{max} are the minimum and maximum limits of reactive power generation for generator 'i' and $|V|_i^{min}$ & $|V|_i^{max}$ are the minimum and maximum limits of voltage magnitude at bus 'i',

d.)Particle Swarm Optimization:

Particle swarm optimization (PSO) is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. It was developed by Eberhart and Kennedy in 1995 [19].

The step by step algorithm of particle swarm optimization for obtaining optimum scheduling of generators is given in this section. Generations are taken as the control variables. The steps are discussed below.

Step1: Create the Fitness function with the power system data including generation cost data and thermal limits.

Step2: Set the limits for control variable. i.e., set minimum and maximum generation limits for generator buses. Number of Particles=Number of control variables.

Step3: Set maximum iteration count and set values for initial and final weights W_{min} and W_{max}.

Step4: Initialize particle size and global best values for control variables. Maximum generation for generator buses is chosen as the initial value for control variables.

Step5: Update the weights using the below formula.
$w=W_{max}-[(W_{max}-W_{min})/MaxIter]*Iter$
where, MaxIter is the maximum iteration count and Iter is the current iteration.

Step6: Update Velocity, Position, local best and global best values. Repeat this for all particles until convergence is obtained or maximum iteration is reached.

Step7: Set global best cost as the fitness function value which gives the generation cost of the system. Global best gives the optimum generation schedule.

3. Simulation and Analysis:

The simulation is done in three parts. First, an ANN is developed to predict the wind speed and calculation of wind power, second the cost of wind power due to variation in wind speed is analyzed and finally, integration of wind farm to IEEE 30 bus test system on different load buses is done and the optimum location is chosen. All the simulations are carried out in MATLAB environment. Neural Network toolbox in MATLAB is used to develop ANN for wind speed prediction.

ANN based wind speed Estimation:

A feed forward back propagation neural network is created having an input layer with 4 neurons, a hidden layer with 48 neurons and an output layer with one neuron. Real time data for training the ANN were collected from Radhapuram village which is the border of Kanyakumari and Tirunelveli districts in the southern part of TamilNadu, India. As this area is one of the places where more wind turbines are installed, the data collected here could be appropriate to train the network. Hourly wind speed data were collected during the period of January 2011 to April 2016. Out of these, 80% of the data were used for training the network and remaining 20% data were used for testing the network. Sample data collected from the site is given in table 1.

Table 1 Sample wind speed data collected from Radhapuram, TamilNadu, India

Date & Time	Wind speed(m/sec)
01/06/2012 01:00	9.4
01/06/2012 02:00	6.9

The time given in this data is split into 4 inputs viz. year, month, day and time (hour) are the inputs to ANN and wind speed is the output. The data are then normalized using equation (7) before training the network and the output of the network was de-normalized to get the wind speed in m/sec.

$$x_i^{norm} = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \qquad (7)$$

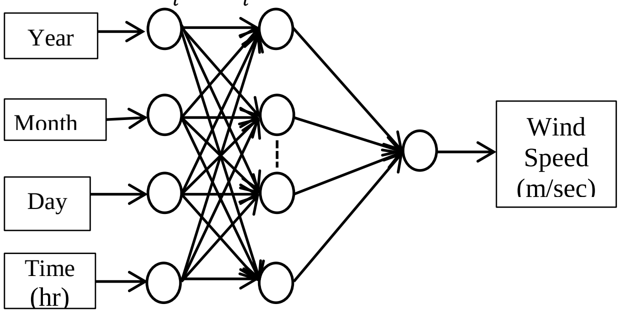

Fig.2. Structure of ANN for wind speed prediction

The performance of the network is assessed using the values of mean squared error (MSE) which is the average squared difference between output and target speed and regression (R) which measures the correlation between output and target. This is shown in table 2 and figure 3.

Table 2 Performance of Developed ANN model

Dataset	Mean Squared Error	Regression
Training	0.01320	0.8431
Testing	0.01360	0.8363
Validation	0.01488	0.8241

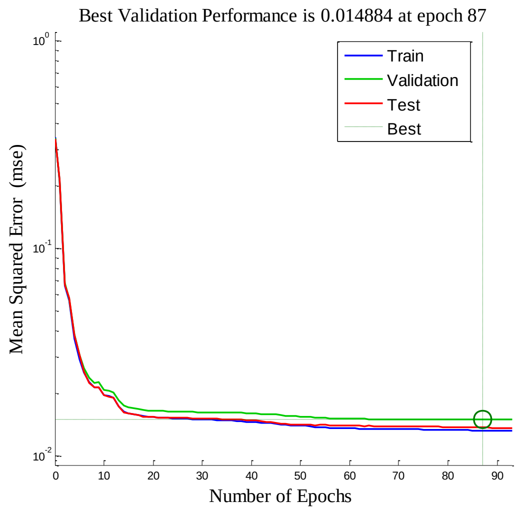

Fig.3. Performance of ANN

The designed ANN provides the output wind speed with minimal error. This network has been used to predict the wind speed for untrained data ie., future data. Wind speed has been predicted for the year 2016. The predicted wind speed is plotted in figure 4.

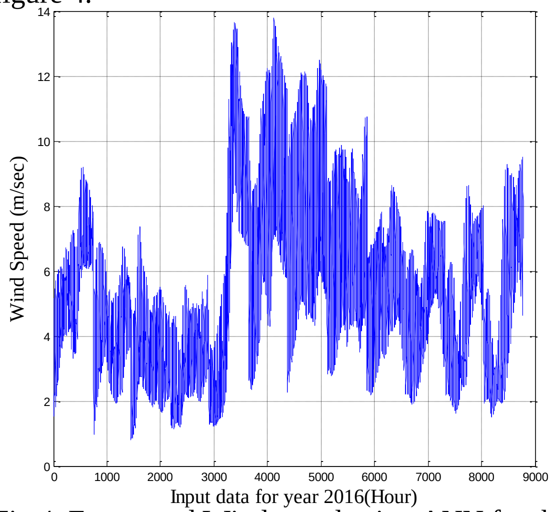

Fig.4. Forecasted Wind speed using ANN for the Year 2016

Wind Power Calculations:

The power generated from the wind turbine is directly proportional to the cube of wind speed (v^3). This power is calculated using equation (8) which shows the wind power is highly influenced by the wind speed and the efficiency of the wind turbine.

$$Pw = \begin{cases} 0, & v_w \le v_{cut-in} \quad or \quad v_w \ge v_{cut-off} \\ 0.5\rho A_{wt} C_p v_w^3\,, & v_{cut-in} < v_w \le v_{rated} \\ P_{rated}, & v_{rated} < v_w < v_{cut-off} \end{cases} \qquad (8)$$

where P_w is the power extracted from wind turbine in watts, ρ is the density of air, A_{wt} is the area covered by the rotor of wind turbine ($A_{wt} = \pi R^2$, R is the radius of rotor), C_p is the performance coefficient ($C_p = C_G C_T$, C_G and C_T are the corresponding coefficients of generator and turbine), v_w is the wind velocity in m/sec, v_{cut-in} and v_{cutoff} are the cut-in and cut-off wind speed for the turbine in m/sec, v_{rated} is the rated wind speed in m/sec and P_{rated} is the rated power of the wind turbine in watts.

To calculate the power generated by the wind turbine for the year 2016 using the predicted wind speed, a turbine from JP wind farm at Radhapuram, Kanyakumari district, India was considered. The rated power of the turbine is 1250 kW and the rated wind speed of the turbine is 12 m/sec. The diameter of the turbine is 64m. The cut-in, cut-off and rated speed of the turbine are 3 m/sec, 14 m/sec and 12 m/sec respectively. The performance coefficient of the wind turbine is 0.42. The air density in that area is taken as 1.2 kg/m^3. Figure 5 shows the predicted power for the year 2016.

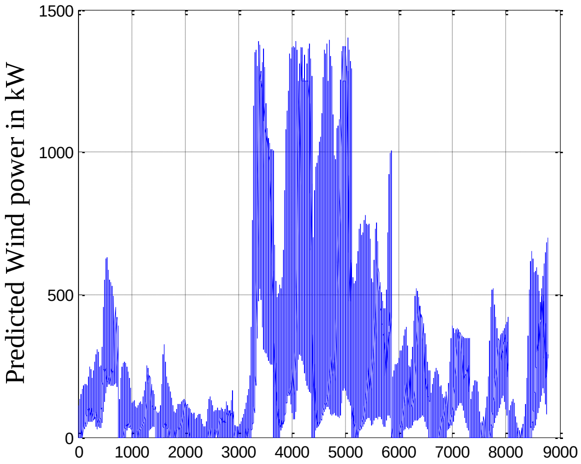

Fig.5. Predicted power for the year 2016

Wind Generation Cost:

The fuel cost for wind generation is zero unlike the fuel cost for a thermal plant, where a quadratic cost equation is used. Since the wind power is a fluctuating quantity, the exact value of scheduled wind farm power cannot be generated. As a result, the cost of generation varies depending on the difference between the scheduled power and actual generated power. Libao Shi *et al*,[3] proposed that the cost of wind energy includes two components. First is the opportunity cost due to wind power shortage and second is the opportunity cost due to wind power surplus compared to scheduled wind power. The total generation cost for wind power is equal to the sum of these two components. This paper utilizes the above concept to calculate the wind generation cost.

The opportunity cost of wind power shortage is the cost generated by utilizing the system spinning reserve to deal with the situation where the actual wind farm power output is less than the scheduled power output. It is considered that the wind farm operator will purchase a certain amount of power to cope with the situation of wind power shortage [3]. The opportunity cost of wind power shortage is given by equation (9).

$$C_L = K_L . Pr(P_w < P_{sch}) . (P_{sch} - E_{Pw<Psch}) \qquad (9)$$

where, C_L is the opportunity cost due to wind power shortage in \$/hr, Pr $(P_w < P_{sch})$ is the probability of wind power shortage occurrence, P_{sch} is the scheduled wind farm output, $E_{Pw<Psch}$ is the expected value of wind farm output power under shortage condition and K_L is the coefficient representing the adequacy of system spinning reserve and the difficulty to dispatch the spinning reserve in \$/kWh.

The opportunity cost of wind power surplus is the cost generated by the environmental benefit loss caused by decreasing wind farm power output [3]. The opportunity cost of wind power surplus is given by equation (10).

$$C_H = K_H . Pr(P_w > P_{sch}) . (E_{Pw>Psch} - P_{sch}) \quad (10)$$

where, C_H is the opportunity cost due to wind power surplus in \$/hr & K_H is a coefficient representing the concerns for environment by local government. The total generation cost for the wind power is given by,

$$C_{wind} = C_L + C_H \qquad (11)$$

To analyze the variation of cost with respect to the scheduled wind farm output for large systems, we have considered a virtual wind farm consisting of 80 units each having a capacity of 1250 kW(The total capacity of the farm is 1250kW x 80 = 100 MW). All the 80 units are assumed to be arranged in zigzag manner so that the power loss from one unit to the other unit can be neglected. The variation of the total generation cost with respect to the scheduled power for various values of cost coefficients is depicted in Figures 6a & 6b.

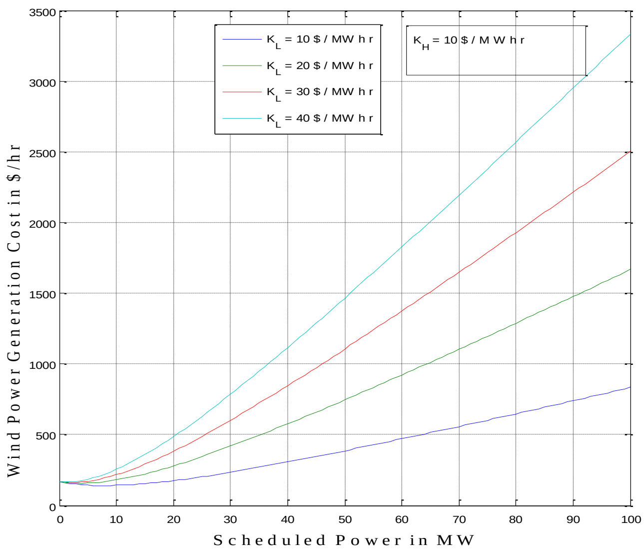

Fig.6a

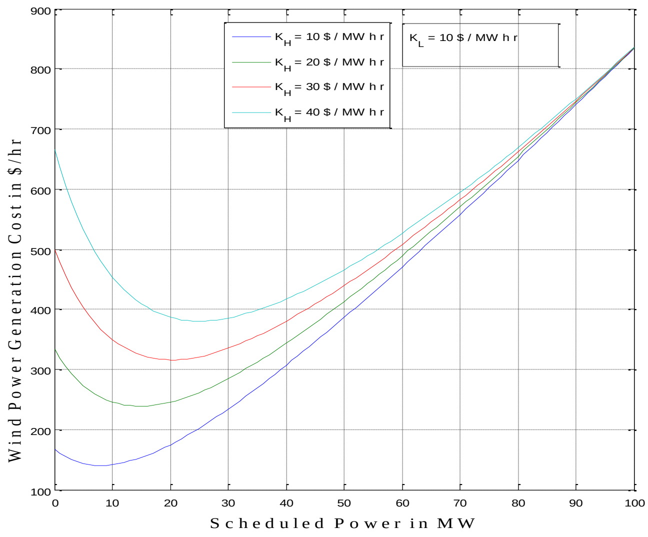

Fig.6b

Fig.6a & 6b. Variation of wind generation cost with respect to scheduled power for different values of cost coefficients

The wind generation cost is calculated based on the predicted wind speed for the year 2016. The results show that the cost of wind power generation gradually decreases with respect to the scheduled power, reaches a minimum value and then starts increasing. Also the cost coefficient K_L has much impact on the generation cost compared to K_H. This shows that more cost will be incurred when there is shortage of wind power generation. This scheduled power for minimum cost is applicable only for standalone wind farms. When the wind farm is integrated to a power system, the scheduled wind power for the minimal generation cost of the entire power system will be different. This scenario is explained in the next section.

IEEE 30 bus Test System:

To analyze the impact of wind energy integration in overall electricity generation cost of the system, IEEE 30 bus test system is considered.

Initially, the optimal power flow is determined without including wind power in the IEEE 30 bus system. The data for IEEE 30 bus system is taken from MATPOWER [20].The OPF is run using conventional technique in MATPOWER as well as using PSO to test the effectiveness of evolutionary algorithm. The parameters of PSO are given as follows: Number of control variables-6(All Generator bus real power excluding slack bus and scheduled wind farm output power), particle size-20, Maximum iteration-100, Inertia weights-W_{min}=0.2 and W_{max}=0.8. The weights update process in PSO is done using the equation (11).

$$W = W_{max} - \frac{W_{max} - W_{min}}{Maximum\ Iteration} * Current\ Iteration \qquad (11)$$

To illustrate the stability of PSO, 10 trial runs have been made and the best result has been chosen. The total generation cost is 8904.7 $/hr using MATPOWER and 8903.9 $/hr using PSO. The convergence characteristics of PSO are shown in figure 7.

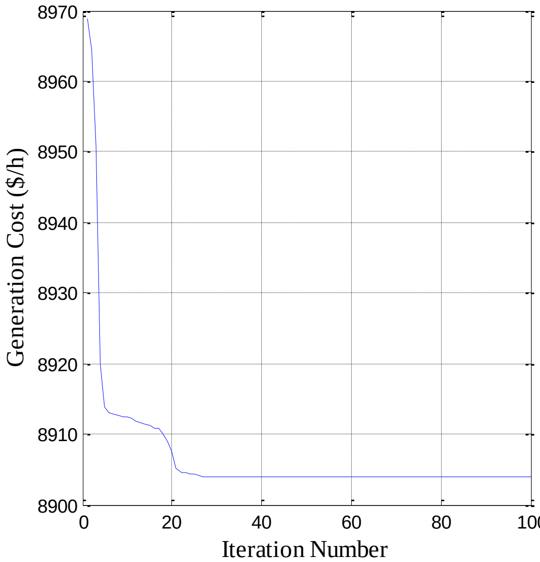

Fig.7. PSO convergence characteristics for IEEE 30 bus system without wind power integration

The result shows that, PSO has slightly better results compared to MATPOWER. This is because, the conventional techniques does not consider about the fixed costs of the cost function. Further if the variation of fixed costs of different generators is more, the results of PSO will be much better. Since cost of wind power generation involves fixed cost in the general cost function, the PSO is used to run the OPF after integrating wind power. Two main assumptions are made for simulations while integrating wind power to the test system. First, the wind speed in all the load stations of IEEE 30 bus system is assumed to be similar and is equal to the wind speed collected at Radhapuram, TamilNadu, India. Secondly, the environmental factors that affect the wind cost are same for all load buses.

The cost coefficients of wind generation, K_H and K_L are set to be 10 $/MWh and 40 $/MWh, respectively, during simulation. The OPF results with wind power integration at different load buses are tabulated in table 3.

Table 3 OPF results for IEEE 30 bus system with wind power integration

Integrated Bus	Scheduled Wind Power(MW)	Total Generation Cost in $/hr
30	41.92	8506.7
29	40.93	8501.5
28	72.10	8397.2
27	60.72	8414.5
26	31.28	8572.0
25	53.55	8449.5
24	59.33	8401.4
23	55.72	8431.8
22	65.77	8376.1
21	66.17	8372.5
20	58.83	8412.2
19	57.39	8414.8
18	54.71	8423.7
17	65.24	8389.6
16	61.15	8420.3
15	62.68	8397.0
14	48.68	8473.2
12	66.66	8405.6
10	69.82	8367.3
9	**71.13**	**8356.4**
7	75.70	8411.6
6	77.71	8542.1
4	73.03	8455.1
3	67.47	8469.7

The results show that the generation cost will be decreased by around 400 $/hr when wind energy is integrated at any bus in IEEE 30 bus system. From table 3, the total generation cost is maximum of 8572 $/hr when wind farm is integrated at bus 26. So bus 26 is not considered as a suitable position for integrating wind power. It is observed that when wind power is integrated at bus 9, the generation cost is minimum of 8356.4 $/hr when compared to that of other load buses. So bus 9 is considered as the first choice for wind farm to be integrated. The convergence characteristic of PSO for wind integration at bus 9 is shown in figure 8.

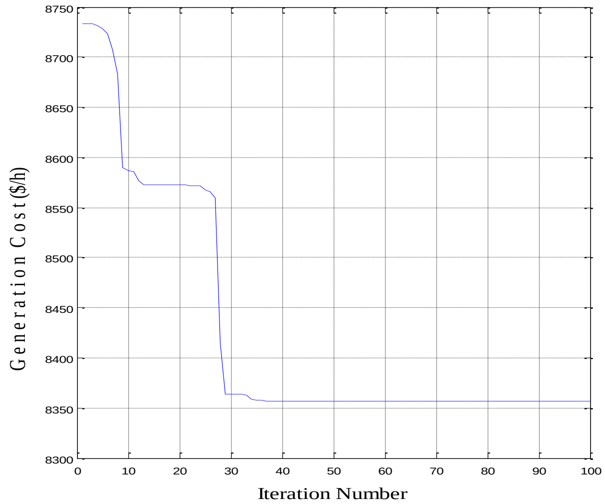

Fig.8. PSO convergence characteristics for IEEE 30 bus system with wind integration at bus 9

4. CONCLUSION:

The work presented in this paper provides a solution to optimal power flow including wind farm integration, where the wind farm generation cost is estimated using opportunistic costs due to wind power surplus and shortage. The fluctuating wind speed plays a major role in the determination of wind power. We used ANN to predict the future wind speed. The work finds that, the wind generation cost is greatly increased when there is shortage of wind power. The work also uses PSO for running OPF on the test system and the most suitable bus for integration of wind farm has been determined. All the simulations are done by assuming same wind speed at all buses. However, in real time, the wind speed at all load buses will not be similar. The scope of the proposed work can be improved further by implementing on a real time system by forming different neural networks (trained with data history from respective load buses) for different wind speed and using respective environmental factors for wind cost estimation.

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