Trends in Life Sciences
An International Peer-reviewed Journal
www.sciencejournal.in

MODIFIED SHUFFLED FROG LEAPING BASED ON OPTIMAL PLACMENT OF WIND TURBINES IN POWER SYSTEM

Ardeshir Arash[1], Hasan Ghadimi[1] and Ali Rajabzadeh[2*]
[1]Department of Engineering, Ardabil Branch, Islamic Azad University, Ardabil, Iran
[2]Young Researchers and Elite club, Ardabil Branch, Islamic Azad University, Ardabil, Iran
*corresponding author, E-mail: rajabzade.ali@gmail.com

ABSTRACT
The Modified Shuffled Frog Leaping (MSFL) algorithm is considered as an optimization technique to power system in this paper. Since the energy losses because of wakes can significantly decrease the energy production and lead to fluctuations in the output power of a wind farm it is desired to determine optimal positions for installing multiple wind turbines. The proposed technique minimizes simultaneously the fuel cost and emission of thermal units by changing location and varying sizes of wind farm. The features and the advantages of MSFL algorithm, such as escaping from local optima traps, global optimization, good robustness, simple mechanism and fast convergence, would make MSFL method as a promising optimization approach. In this paper the wind farm in form of doubly fed induction generator penetrating is formulated into a power system.

KEY WORDS: Wind Farms, MSFL, Optimal Placement

INTRODUCTION

Although wind power energy generation in 2010 was evaluated to be just about 2.5 percent of worldwide electricity usage, wind turbines are considered a preliminary technology with many experts suggesting that we're approaching the theoretical limit of individual wind turbine efficiency. Therefore, researchers are now looking at new approaches to wind farm design to increase the power output of wind farms. Where most wind farms employing horizontal-axis wind turbines, the standard propeller such as turbines most commonly found in wind farms around the world - space the individual turbines around seven rotor diameters apart, a recent study found that spacing of at least 15 rotor diameters apart provided the most cost-efficient power generation. But even though looking for the turbines out increases the cost-efficiencies by allowing for fewer individual turbines, it also lowers the power output of a given plot of land.

Wind energy occupies a prominent position among renewable energy sources, and will gain in significance as governments worldwide strive to reduce the environmental footprint in the energy sector. Following this trend, optimal wind turbine placement on a selected wind farm site is of major importance, since it can lead to a remarkable increase in the produced power (Demeo, 2005). While dense configurations appear as an intuitive solution, the so called wake effect is a known side-effect of tight spacing shadowing. It is caused by the fact that when extracting energy from the wind, each turbine makes a cone of more turbulent and slower air behind it, and hence the wind speed encountered by downstream wind turbines decreases, leading to reduced energy yield (Grady, 2005). The problem of maximizing the power produced by a wind farm by properly locating the wind turbines so as to minimize the wake effect (taking into account the physical constraints), is a typical optimization problem. Due to the highly nonlinear dependency of the produced power on the wind we resort to randomized optimization techniques that allow representing wind turbines with detailed and nonlinear models and/or include non-convex cost functions in the optimization process. In this framework, (Bansal, 2005; Patel, 1999; Wood, 1996; Ghadimi, 2014) and references therein, addressed the problem in discrete space by considering a gridded version of the wind farm site and designating the corresponding cell centers as candidate wind turbine locations. A simplified wind turbine model was used and genetic algorithms were employed to solve the optimization problem. This approach was hampered though by the conservatism introduced by the discrete space optimization.

The advantage of wind power in economic is very low operation and maintenance cost. When wind farm is built to generate electricity, it can produce continually electricity into power system without many times of interruption (Ayotte, 1994; Jeksin, 1993). Moreover, wind energy system operations do not generate air or water emissions and do not produce dangerous waste. Nor do they deplete natural resources such as coal, oil, or gas, or require significant amounts of water during operation. Wind's contamination-free electricity can help reduce the environmental damage caused by power generation from all country (Frandsen, 1991). Also, in (Ahadi *et al*., 2014; Ghadimi, 2014) the author has described some problems in power system in market environment.

For this purpose, the Modified Shuffled Frog Leaping (MSFL) is proposed in this paper to find appropriate location of wind power. The features and the advantages of MSFL algorithm, such as escaping from local optima traps, global optimization, good robustness, simple mechanism and fast convergence, would make MSFL method as a promising optimization approach. The effectiveness of the proposed technique is applied over IEEE 30 bus power system which considers the fuel cost and emission for minimization simultaneously. Achieved results demonstrate the efficiency of the proposed technique.

PROBLEM FORMULATION

The objective of environmental/economic power dispatch with varying location and sizing of wind farm is to minimize the economic and environmental cost function of power system while satisfying various equality and inequality constrains (Grady, 2005).

Objective Function

Minimization of generator cost

The total US$/h fuel cost f(PG) is presented as follow:

$$f(P_{Gi}, P_w) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + d_i P_w \tag{1}$$

Where ai, bi, ci and di are the cost coefficients of the ith generator thermal units and wind farm, and PGi and Pw are the real power output of the ith generator thermal units and wind farm at bus w . N is the number of generators which can be defined as:

$$P_{Gi} = \left[P_{G1}, P_{G2}, \ldots, P_{GN}, P_W\right]^T \tag{2}$$

Minimization of environmental emission

The collected ton/h emission E(PG) of atmospheric pollutants such as sulfur oxides SOX and nitrogen oxides NOX caused by fossil-fueled thermal units can be expressed as

$$e(P_{Gi}, P_w) = \sum_{i=1}^{N} \begin{matrix} 10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \\ + \xi_i \exp(\lambda_i P_{Gi}) + \rho P_W \end{matrix} \tag{3}$$

Where αi, γi, βi, ζi, λi and ρ are coefficients of the ith emission characteristics of thermal units and wind farm.

Constraints

Generation capacity constraints

For stable operation, real power output of each generator is restricted by lower and upper limits as follows:

$$\begin{aligned} &P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, N \\ &P_w^{\min} \le P_w \le P_w^{\max}, 1 \le w \le N_B \end{aligned} \tag{4}$$

Where, NB is the number of buses.

Power balance constraints

Power balance is an equality constraint. The total power generation must cover the total demand PD. Hence,

$$\sum_{i=1}^{N} P_{Gi} + P_W - P_D - P_L = 0 \tag{5}$$

Then, power loss in transmission lines can be calculated as

$$P_{loss} = \sum_{k=1}^{NL} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)\right] \tag{6}$$

Where,
Vi and Vj : the voltage magnitudes at bus i and j .
δi and δj : the voltage angles at bus i and j .
Line loading constraints
For secure operation as follows:

$$S_{Li} \le S_{Li}^{\max}, i \in N_L \tag{7}$$

Where,
Sl and L N : The transmission line loading and the number of transmission lines.
Formulation of Multiobjective optimization
Aggregating the objectives and constraints, the problem can be mathematically formulated as a nonlinear constraint multi-objective optimization problem as follows (Mosetti *et al*., 1994; Katic *et al*., 1986).

$$Minimiza[\,f(x,u), e(x,u)] \tag{8}$$

Subject to:

$$\begin{aligned} g(x,u) &= 0 \\ h(x,u) &\le 0 \end{aligned} \tag{9}$$

Where,
g(x,u): the equality constraints ,
h(x,u): the system inequality constraints.

Multiobjective optimization principle
For a multi-objective optimization problem, any two solutions x1 and x2 can have one of two possibilities:
One dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution x1 dominates x2 if the following two conditions are satisfied (Grady *et al*., 1986):

$$\forall i \in \{1,2,...,N_{obj}\}: f_i(x_1) \le f_i(x_2)$$

$$\exists i \in \{1,2,...,N_{obj}\}: f_i(x_1) \le f_i(x_2) \tag{10}$$

If any of the above condition is violated, the solution x1 does not dominate the solution x2. If x1 dominates the solution x2, x1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute Pareto-optimal set. This set is also known as Pareto-optimal front (Serrano *et al*., 2009; Marmidis *et al*., 2008).

MSFL TECHNIQUE

Shuffled Frog Leaping (SFL) algorithm, has been introduced by Eusuff and Lansey for water distribution system optimization, is a meta-heuristic for solving optimization problems (Noakes and Kozera, 1999) SFLA is a decrease based stochastic search method that begins with an initial population of frogs whose characteristics, known such as memes, represent the decision variables. For this algorithm, the individual frogs are not the important parts; rather they are seen as hosts for memes and described as a memetic vector (Noakes and Kozera, 2003a). The algorithm uses

Trends in Life Sciences
An International Peer-reviewed Journal
www.sciencejournal.in

memetic evolution in the form of influencing of ideas from one individual to another in a local search. In SFL, the population consists of a set of frogs (solutions) partitioned into subsets, referred to as memeplexes. Actually the different memeplexes are considered as different cultures of frogs, each performing a local search (Noakes and Kozera, 2003 b)

Hence, the positions of the frogs are presented as:

$$D_i = rand \times (X_b - X_g) \tag{6}$$

And for new position:

$$X_{i+1} = X_i + D_i, -D_{\max} \leq D_i \leq D_{\max} \tag{7}$$

Where,
rand = random number between 0 and 1.
Dmax = the maximum allowed change in a frog's position.
Modified Shuffled Frog Leaping Algorithm
problems. However, it is difficult for SFLA algorithm to overcome local minima when handling some complicate functions (Noakes and Kozera, 1999). MSFLA starts with an initial population of "X" frogs created randomly like other evolutionary algorithms. The whole population of frogs is then partitioned into subsets referred to as memeplexes. The various memeplexes are considered as different cultures of frogs. And they are located at different places in the solution space (i.e., global search). Each culture of frogs performs a deep local search. Within each memeplex, the individual frogs hold information that can be influenced by the information of their frogs within their memeplex, and evolve through a process of change of information among frogs from different memeplexes (Noakes and Kozera, 1999). After a defined number of evolutionary steps, information is passed among memeplexes in a shuffling process. The local search and the proposed processes continue until a defined convergence criterion is satisfied.
It is necessary to note that the mutation vector dimension is equal to the memeplexes number. Therefore, a position changing formula turns to the following form.

$$D_i = rand \times C \times (f(X_b) - f(X_w)) \times (X_b - X_w) \tag{8}$$

And for new position:

$$X_{i+1} = X_i + D_i \tag{9}$$

Where,
C € [0, Cmax],
Cmax = case dependant upper limit
f(Xb)= The best fitness functions that are found by the frogs in each memeplexs.
f(Xw)= The worst fitness functions that are found by the frogs in each memeplexs.
Similar to the original SFL, if the process produces a better solution, the worst frog is replaced by the better one.
Reducing Pareto set by FCM clustering
Fuzzy c-means (FCM) is a data clustering technique in which a data set is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree (Frandsen, 1991). For example, a certain data point that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another data point that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, 1 \leq m < \infty \tag{14}$$

Where m is any real number bigger than 1, u ij is the degree of membership of x i in the cluster j , x i is the ith of d-dimensional scaled data, c j is the d-dimension center of the cluster, and $\| \; \|$ is any norm imparting the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u ij and the cluster centers c j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - c_i\|}{\|x_i - ck\|} \right)^{\frac{2}{m-1}}} \tag{15}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{16}$$

This iteration will stop when maxij $\left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right\} < \varepsilon, \varepsilon$ is a termination criterion between 0 and 1, whereas k is the iteration step. This procedure converges to a local minimum or a saddle point of Jm.

By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set. Once the group centers have been obtained, the next solution to each center is selected, and the other solutions are eliminated. Reducing Pareto set by the FCM method is shown as Fig 2.

Best Compromise Solution

After obtaining the Pareto-optimal solution, the decision maker may need to choose one best compromised solution according to the specific preference for different applications. However, because of the inaccurate nature of human judgment, it is not possible to explicitly define what is really needed.

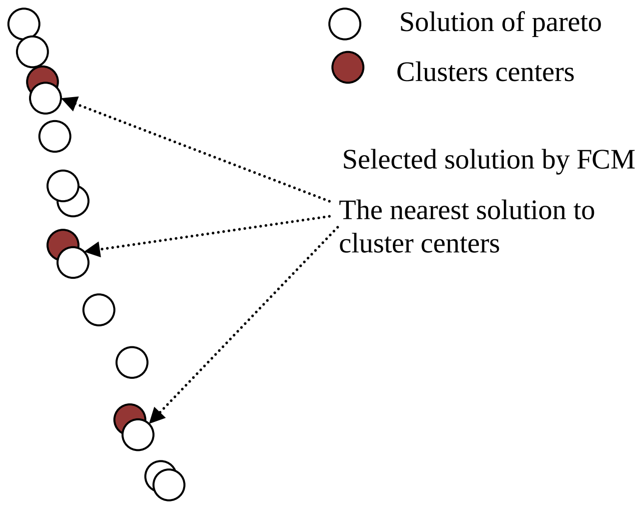

Figure 1. The FCM method for reducing Pareto set

Thus, fuzzy set is defined here to handle the dilemma. Here a linear membership function i u is defined for each of the objective functions i F:

$$u_i = \begin{cases} \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, F_i^{\max} > F_i > F_i^{\min} \\ 1, F_i \le F_i^{\min} \\ 0, F_i \ge F_i^{\max} \end{cases} \tag{17}$$

In the above formulation, $F_i^{\max}$ and $F_i^{\min}$ is the value of the maximum and minimum in the objective functions, respectively. It is evident that this membership function indicates the degree of achievement of the objective functions. For every non-dominated solution k, the membership function can be normalized as follows:

$$u^k = \frac{\sum_{i=1}^{O} u^k i}{\sum_{k=1}^{S}\sum_{i=1}^{O} u^k i} \tag{18}$$

Where,
O= The number of objective functions
S= The number of non-dominated solutions.
The solution with the maximum membership uk can be seen as the best compromised solution.

Implementation
The proposed technique has been developed in order to make it suitable for solving nonlinear constraints optimization problem. A computation process will check the feasibility of the candidate solution in all stage of the search process. This ensures the feasibility of the non-dominated solution.

The proposed MSFL is a recently developed powerful evolutionary algorithm, inspired from the mating process of honey bees, for solving single or multi-objective optimization problems with real-valued or discrete parameters (Grady *et al*., 2005). In this paper, a new enhanced version of SFL algorithm named Modified Shuffled Frog Leaping (MSFL) is proposed for finding optimal location of wind power. The proposed MSFL technique is tested over IEEE a 30-bus 6-generator test system considering the problem objective functions. More information of the proposed power system is presented in (Frandsen, 1991). . The values of fuel cost and emission coefficients are given in Table I.

TABLE I. GENERATING UNIT FUEL COST AND EMISSION COEFFICIENTS.

Unit	G_1	G_2	G_3	G_4	G_5	G_6
P_{min}	0.05	0.05	0.05	0.05	0.05	0.05
P_{max}	0.5	0.6	1.00	1.2	1.00	0.6
Cost						
A	10	10	20	10	20	10
B	200	150	180	100	180	150
C	100	120	40	60	40	100
Emission						
α	4.091	2.543	4.258	5.326	4.258	6.131
β	-5.55	-6.04	-5.09	-3.55	-5.09	-5.55
γ	6.490	5.638	4.586	3.380	4.586	5.151
ζ_i	2e-4	5e-4	1e-6	2e-3	1e-6	1e-5
λ_i	2.857	3.333	8.000	2.000	8.000	6.667

WIND FARM
Wind farm consist of a number of wind turbines connected to bus of power system topology through power transformer. Wind turbines use a doubly-fed induction generator (DFIG) consisting of a wound rotor induction generator and an AC/DC/AC IGBT-based PWM converter. For example, a wind farm is shown in Fig. 3. The stator winding is connected directly to the 60 Hz grid while the rotor is fed at variable frequency through the AC/DC/AC converter. The DFIG technology allows extracting maximum energy from the wind for low wind speeds by optimizing the turbine speed, while minimizing mechanical stresses on the turbine during gusts of wind. The optimum turbine speed producing maximum mechanical energy for a given wind speed is proportional to the wind speed.

For optimization problem in this paper the cost and emission coefficients of wind farm are zero. Large wind turbine is selected to produce electric power up to 1.5 MW. Minimum capacity of wind farm is set as 4.5 MW or 3 wind turbines and Maximum capacity of wind farm is set as 105 MW or 70 wind turbines. These wind turbines run at speed of wind as 12 m/s.

SIMULATION RESULT

At first step the best fuel cost and emission of power system is calculated without wind farm. Accordingly the proposed MSFL is applied to power system in situation that the wind farm is not penetrated into power system network. The achieved result is presented in Table 2.

TABLE II. RESULTS OF BEST SOLUTION WITHOUT WIND FARM

Unit (MW)	**Best solution**
P_{G1}	102.245
P_{G2}	75.625
P_{G3}	18.663
P_{G4}	34.716
P_{G5}	24.264
P_{G6}	32.398
Total of thermal units (MW)	287.911
Fuel Cost ($/h)	835.513
Emission (ton/hr)	0.241

For the second step, the proposed optimization problem is solved by MSFL technique considering the wind farm in power system network. The achieved results demonstrate the optimum location of wind farm and the capacity of that. Table. 3, shows the achieved results of simulation.

Capacity of wind farm is 96.33 MW or approximately 66 wind turbines. This value is high penetration of wind farm on test system. Fig. 4 shows the best solution on tradeoff surface with wind farm in power system network. According to the presented tables it can be said that connecting the wind power could reduce the fuel cost and emission of pollution as 314.021 and 0.028, respectively. Also, Best solution on tradeoff surface with wind farm in power system network is presented in Fig. 4.

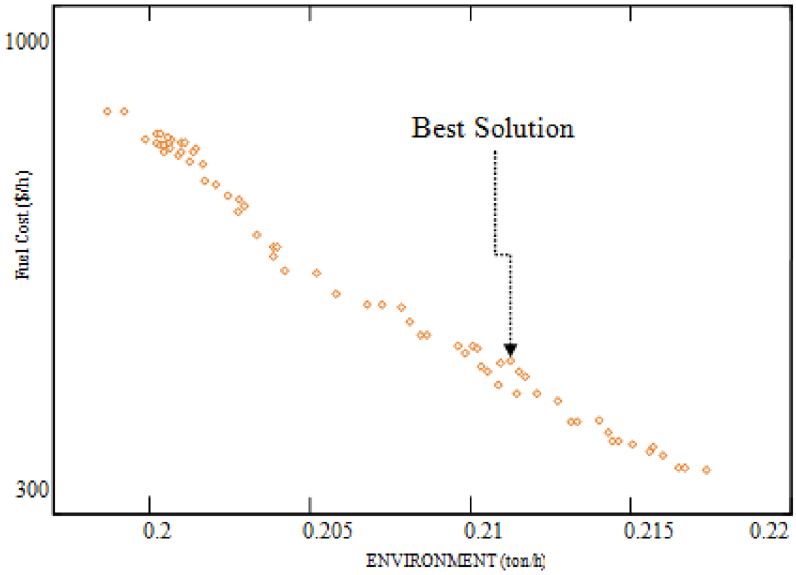

Figure2. Best solution on tradeoff surface with wind farm in power system network

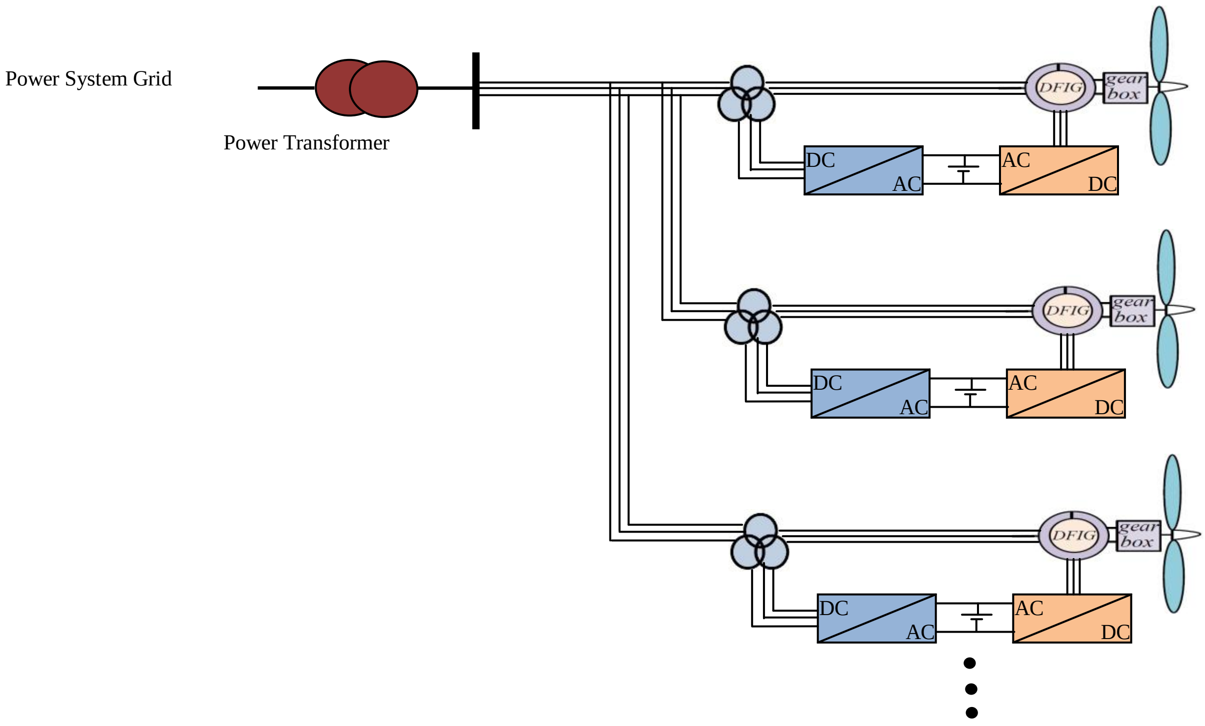

Figure 3. Wind farm with many wind turbines connect to power system

Accordingly, the best location of wind farm is calculated to bus 21 considering the best solution of cost and emission. Fig. 5 shows the proposed power system with wind farm connection.

Figure 4. Results of best solution with wind farm

Unit (MW)	**Best solution**
P_{G1}	42.745
P_{G2}	28.921
P_{G3}	28.635
P_{G4}	28.145
P_{G5}	18.603
P_{G6}	26.993
Total of thermal units (MW)	174.042
Fuel Cost ($/h)	518.84
Emission (ton/hr)	0.2097
	Wind farm
Location (b\Bus)	21
Size (MW)	98.24

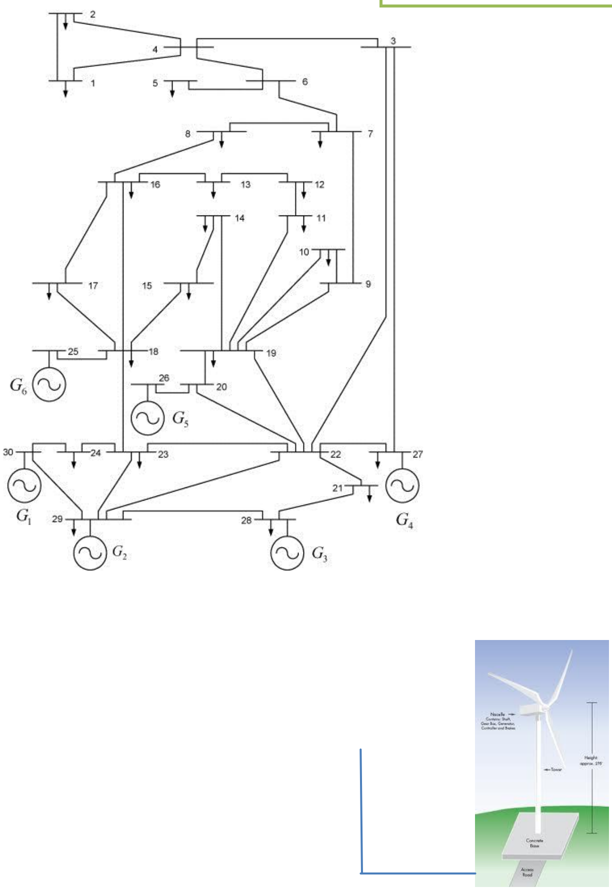

Figure 5. Position of wind farm on power system

CONCLUSION

In this paper, Improved Honey Bee Mating Optimization (MSFL) is applied to power system to find best location and sizing of wind farm on through minimization of generations economic and emission. Small scale wind turbines can be used in domestic, community and smaller wind energy projects and these can be either stand-alone or grid-connected systems. Wind farm is formulated in form of doubly fed induction generators to inject electric power into power system. Also, the proposed MSFL consists of the high ability, great potential and good perspective for solving optimization problems. In this paper connecting the wind farm in optimum sizing and location could reduce the fuel cost and emission.

REFERENCES

Ahadi A., Ghadimi N. and Mirabbasi D. (2014). An analytical methodology for assessment of smart monitoring impact on future electric power distribution system reliability. *Complexity.* doi: 10.1002/cplx.21546.

Ayotte K (1994). The impact of turbulence schemes on predictions of the mixed spectral finite-difference model of flow over topography, Boundary-Layer Meteorology.

Bansal R (2002). On some of the design aspects of wind energy conversion systems. *Energy Convers Manag.* 43(16), pp. 2175-87.

Demeo E. (2005). Wind plant integration. *Power Energy Magazine, IEEE.* 3(6). 38-46,

Frandsen S (1991). On the wind speed reduction in the center of large clusters of wind turbines. Proc. European Wind Energy Conference. pp. 375-80.

Ghadimi N. (2014). A new hybrid algorithm based on optimal fuzzy controller in multimachine power system. *Complexity.* doi: 10.1002/cplx.21544.

Ghadimi N. (2014). An adaptive neuro-fuzzy inference system for islanding detection in wind turbine as distributed generation. *Complexity.* doi: 10.1002/cplx.21537.

Grady S (2005). Placement of wind turbines using genetic algorithms, Renew Energy (Elsevier),

Grady S.A., Hussaini M.Y. and Abdullah M.M. (2005). "Placement of wind turbines using genetic algorithms", *Renewable Energy*. 30(2): 259-270.

Jenkins N (1993). Electrical design of wind farms, Proceedings IEEE/ NTUA Athens Power Tech Conference, *Athens, Greece,* pp. 990-994.

Katic I., Højstrup J. and Jensen N.O. (1986). "A simple model for Cluster Efficiency", *Proc. European Wind Energy Conf.*

Marmidis G. (2008). Optimal placement of wind turbines in a wind park using Monte Carlo simulation. *Renewable Energy*. 33:1455-1460,

Marmidis G., Lazarou S. and Pyrgioti E. (2008). "Optimal placement of wind turbines in a wind park using Monte Carlo simulation", *Renewable Energy*. 33:1455- 1460.

Mosetti G., Poloni C. and Diviacco B. (1994). "Optimization of wind turbine positioning in large wind farms by means of a genetic algorithm". *J. Wind Engineering Industrial Aerodynamics.* 51(1):105-116.

Noakes L. and Kozera R. (1999). "A 2D Leap-Frog algorithm for optimal surface reconstruction", *Proc. 44th Annual Meet. Opt. Eng. SPIE'99, III-3811*. 317–328.

Noakes L. and Kozera R. (2003a). "Denoising images: Non-linear leap-frog for shape and lightsource recovery", Chapter in Theoretical Foundations of Computer Vision Geometry, Morphology and Computational Images, pp: 419–436. *Lecture Notes Computer Sci.* 2616.

Noakes L. and Kozera R. (2003b). "Nonlinearities and noise reduction in 3- ource photometric stereo", *J. Math. Imag. Vis.* 2(19): 119-127.

Patel M. (1999). Wind and Power Solar Systems, CRC Press, Boca Raton.

Wood N. (1996). Wind flow over complex terrain: a historical perspective and the prospect for large-eddy modeling, Boundary-Layer Meteorology.

