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Firefly Algorithm Based Multi-Objective Optimal Power Flow in the Presence of Wind Power

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Abstract: This study emphasizes solution to the multi objective Optimal Power Flow (OPF) problem in power system embraced with wind power. The OPF problem is formulated and analyzed for two different objectives such as minimization of fuel cost, minimization of active power loss and voltage deviation. The objective function for minimization of fuel cost is incorporated with wind speed variability in terms of over and underestimation cost during the estimation of wind power generation cost. Firefly Algorithm (FA) based optimization technique is used and results were compared with modified Cuckoo Search algorithm and modified particle swarm optimization for solving OPF incorporated with wind power. Due to the penetration of variable wind power generation into the existing power system, voltage deviation issues occur and it may lead to voltage collapse. In order to maintain voltage stability of connected power system network, reactive power management of grid connected windfarms using Static Var Compensator (SVC) is required. The concept of minimizing active power losses while maintaining desirable voltage profile in all buses along with optimized SVC rating under variable wind power penetration has been evaluated as multi objective function. Optimal values for SVC setting are searched using Firefly algorithm in a modified IEEE 30 bus system and its capability is demonstrated by comparison between power losses of the system before and after optimization. The results depict the importance of wind scheduling on total system cost and the need of optimum reactive power compensation to maintain voltage profiles of the grid connected power system.

Key words: Optimal power flow, Firefly algorithm, wind power, reactive power compensation, fuel cost

INTRODUCTION

The pressure created due to the decrease of fossil fuels and increase in energy demand has created the need to study the steady state effect of wind energy interconnection with conventional power networks. Most of the studies on wind energy so far were focused on either a standalone operation or transient analysis of the electromechanical system. The OPF is an important tool for power system planning and operation in order to achieve economic and secure operation of the power system while satisfying equality and inequality constraints. The problem of optimal reactive power allocation with penetration of wind power is a highly nonlinear and multimodal. Nonlinear programming approaches used to solve constraint optimizations have many disadvantages such as insecure convergence properties and complex computations. These gradient based methods many converge to local minimal point. Perhaps, there is no criterion to decide whether the local best solution is also the global best.

In the last two decades, many new algorithms such as Swarm optimization, Neural Networks, Ant-colony optimization, Differential Evolution, Bat algorithm, Evolutionary Programming, Genetic Algorithm, Simulated Annealing, Tabu Search, Firefly algorithm and cuckoo search have emerged with great potential for engineering optimization problems (Fister *et al*., 2013; Kennedy *et al*., 2001; Yang *et al*., 2010) among these multi-agent meta-heuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have gained huge popularity. Heuristics algorithms like GA and evolutionary programming were introduced for solving the OPF problem. The results from these methods encouraged the researchers to work on these methods. However, the modern researchers recognized some drawbacks in GA performance which cause deprivation in the efficiency of the system, i.e., the parameters are being optimized with high correlation while the performance and the search capability also get decreased by the premature convergence of GA (Yuryevich and Wong, 1999; Fogel, 2006; Yang *et al*., 2013).

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Firefly algorithm is a meta-heuristic optimization algorithm introduced by Yang (2014) is used in this research. Many researchers solved OPF problem for standard IEEE 30 bus system using various bio inspired evolutionary computation techniques. Prior researchers have used reactive power control strategies in thermal power systems for voltage and power factor control (Kayikci and Milanovic, 2007), flicker mitigation (Meegahapola *et al*., 2010), enhancement of voltage stability (Devaraj and Roselyn, 2010) and system loss/cost minimization (Rao *et al*., 2013). It is obvious that wind penetration levels are not constant and the production level of wind power plant is based on its operating curve.

Minor community of research people contributed to OPF model incorporated with wind power. The OPF problem has not been solved for multi objective problems such as minimization of active power loss and voltage deviation, fuel cost for the power system in the presence of wind power. This study formulates above mentioned problem and presents a solution to it through a novel optimization technique of Firefly algorithm which is then compared with the results obtained by modified particle swarm optimization and modified cuckoo search to demonstrate its effectiveness.

The Newton-Raphson based approach is used to solve the OPF problem. The problem is formulated as an optimization problem with mild constraints. The existing methods of power quality improvement measures are based on applications of power electronic converter. Various reactive power compensators are available like Static Synchronous Compensator (STATCOM), Static VAR Compensator (SVC), Thyristor Controlled Series Compensator (TCSC), Static Synchronous Series Compensator (SSSC), etc. (Hingorani and Gyugyi, 2000) are used to supply reactive power.

In this research, OPF has been solved for the objective of fuel cost minimization of power system incorporated with wound rotor induction generator based wind energy system. Estimation of wind power generation cost is carried out by incorporating wind speed variability in terms of over and underestimation cost.

Solution of OPF problem for minimization of fuel cost or active power loss as major objective function leads to the setting of control variables which may result in undesirable voltage profile at different bus bars. Penetration of variable wind power generation into the existing power system also causes voltage deviation issues and it may lead to voltage collapse. In order to maintain voltage stability of connected power system network, reactive power management of grid connected windfarms using Static Var Compensator (SVC) is required. The concept of minimizing active power losses while maintaining desirable voltage profile in all buses along with optimized SVC rating under variable wind power penetration has been evaluated as multi objective function.

The results depict the importance of wind scheduling on total system cost and the need of optimum reactive power compensation to maintain voltage profiles of the grid connected power system.

MATERIALS AND METHODS

Modelling of wind speed and induction generator: A wind turbine consists of a rotor mounted to a nacelle and a tower with two or more blades mechanically connected to an electric generator. The output power or torque of a wind turbine is determined by several factors. Among them important factors are turbine speed, rotor blade tilt, rotor blade pitch angle, size and shape of turbine, area of turbine, rotor geometry whether it is a HAWT or a VAWT and wind speed. A relationship between the output power and the various variables constitute the mathematical model of the wind turbine. A mathematical model of wind turbine primarily depends upon modelling of wind speed. The actual mechanical power P_w extracted by the rotor blades in watts is the difference between the upstream and the downstream wind powers:

$$P_w = \frac{1}{2}\rho A v_w \left(v_u^2 - v_d^2\right) \tag{1}$$

Where:

- v_u = The upstream wind velocity at the entrance of the rotor blades in ms $^{-1}$
- v_d = The downstream wind velocity at the exit of the rotor blades
- v_w = The velocity at rotor blade in ms $^{-1}$
- A = The area through which the wind in this case is flowing
- ρ = The density of air

which may be simplified as follows:

$$P_w = \frac{1}{2}\rho A v_u^3 C_p \tag{2}$$

Where:

$$C_p = \frac{\left(1+\frac{v_d}{v_u}\right)\left(1-\left(\frac{v_d}{v_u}\right)^2\right)}{2}$$

The expression for C_p in Eq. 2 is the fraction of upstream wind power captured by the rotor blades. Modelling of wind speed is carried out by considering

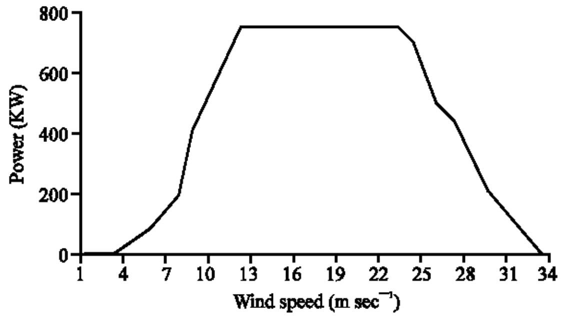

Fig. 1: Wind turbine output power vs wind speed

Reyleigh wind speed distribution and on correlation matrix which is obtained from previously known wind speed series (Feijoo *et al*., 1999) (Fig. 1).

Modelling requirements of wind turbine generators for power flow analysis is elucidated by Vittal and Ayyanar (2013). Practically, type 1 wind turbine generators can be characterized as P-Q bus. While evaluating the influence of wind farm on the steady state performance of the power system it is not necessary to model each turbine in a wind farm. Output of the wind farm can be equivalenced.

Development of SVC models and their execution in load flow and optimal power flow algorithms are considered in (Ambriz-Perez *et al*., 2000). The SVC can be modelled as a continuous, variable shunt susceptance. In order to obtain specified voltage magnitude while satisfying constraint conditions SVC value should be adjusted.

Mathematical problem formulation

Cost associated with wind power: Wind is intermittent in nature and the output power of wind energy conversion system may not be equal to the estimated output power which is scheduled to transfer with connected grid. If the windfarm is owned by the system operator, then there will not be penalty for deficiency of predicted wind power supply. Now, there can be two cases either the cost associated with wind power shortage due to overestimation or cost associated with wind power surplus because of underestimation. The cost of overestimation depends on probability of occurrence of wind power deficiency for a given scheduled power. In order to maintain power balance, power is bought from alternate energy sources or load shedding is employed. Therefore, a penalty term is introduced for shortage of wind power by considering reliability and economic concerns. The cost of underestimation depends on the amount of surplus wind power available and the probability of surplus occurrence. Underestimation leads to obligatory reduction of output power which corresponds to wastage of available wind energy capacity and negative environmental impact. Actually, the cost associated with surplus wind power is not a real cost, it is a penalty term for the non-utilization of available resources. Let:

P_{shwp} = Scheduled windfarm output power
P_r = Rated electrical output of wind generator
C_{ov} = Cost of overestimation of available wind power
C_{un} = Cost of underestimation of available wind power

Now, the cost associated with electricity generated by wind energy is expressed as:

$$\text{Cost of wind generated electricity} = \text{Cov} + \text{Cun} \tag{3}$$

Mathematically, C_{ov} and C_{un} can be expressed as follows:

$$\text{Cov} = \text{PCov} \times \int_0^{\text{Pshwp}} \left(P_{shwp} - w\right) \times f_w(w) \times dw \tag{4}$$

$$\text{Cun} = \text{PCun} \times \int_{\text{Pshwp}}^{\text{Pr}} \left(w - P_{shwp}\right) \times f_w(w) \times dw \tag{5}$$

Where:

Pc_{ov} = Penalty cost of buying power from reserve per \$/KWh due to overestimation of wind power
Pc_{un} = Penlty cost for environmental benefit loss per \$/KWh due to underestimation of wind power
w = wind power output
$f_w(w)$ = Probability density function of wind power output

Minimization of fuel cost: The objective function for OPF problem is to minimize the overall cost of running conventional generations and cost of wind generation for optimal scheduling. Combined cost of thermal as well as wind generation is determined by considering the fuel cost curve of thermal generators as quadratic equation added with cost of wind generation by considering the effect of overestimation and underestimation. Fuel cost curve of thermal generators without valve point effect is given by:

$$C\left(P_{gi}\right) = a_i P_{gi}^2 + b_i P_{gi} + \gamma_i \tag{6}$$

where, a_i, b_i, γ_i are known as cost coefficients which depends on fuel used and input output curve of the ith conventional generator. The P_{gi}= real power generated at ith bus objective function of OPF problem is given as:

$$\min H\left(P_{gi}, P_{shwp}\right) = \sum C\left(P_{gi}\right) + \text{Cov} + \text{Cun},\ \ i \in N_g \tag{7}$$

Minimization of active power loss and voltage deviation: To improve the voltage profile and to minimize the active power loss of a benchmark system with wind penetration in the network, the overall objective function is given by:

$$\min F_Q = \sum_{k \in N_L} AP_{kloss} + B\sum_{i=1}^{Nb}\left|V_i - V_{ref}\right| \quad (8)$$

Where:

A, B = The adjustable weighting parameters of the objective function; A and B are adjusted to obtained reduced total system loss and improve voltage profile

V_i = The voltage at bus 'i'

V_{ref} = The reference voltage of the buses which is taken as 1pu

N_L = No. of lines

P_{kloss} = The power loss in the kth transmission line

System constraints

Equality constraints: The transmission network is modeled by a power balance equation at each node. The algebraic sum of the active and reactive powers injected into each node i must be equal to zero:

$$P_i - V_i \sum_{j \in N_b} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 i \in N_b \quad (9)$$

$$Q_i - V_i \sum_{j \in N_b} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0 i \in N_b \quad (10)$$

Where:

P_i = The active power injected at bus 'i'

Q_i = The reactive power injection at 'i'

N_g = No. of conventional generator buses

N_b = No. of buses in the system

G_{ij} = The mutual conductance between bus i and bus j

θ_{ij} = The phase angle between bus i and bus j

B_{ij} = The mutual susceptance between bus i and bus j

$$\sum_{i=1}^{Nw} P_{WGi} = P_{wind}, \; i \in Nw \quad (11)$$

Where:

P_{WGi} = The active power output of wind farm i

P_{wind} = The total wind power generation

N_w = The total number of wind farms in the system

Inequality constraints: The conventional generation units have maximum and minimum generating limits, both in real and reactive power, beyond which is not feasible to generate for technical or economic reasons, similar restriction do apply for wind farms. Bus voltage magnitude limits for this study are given by:

$$V_i^{min} \le V_i \le V_i^{max} i \in N_B \quad (12)$$

where, N_b represents the total number of Buses. Our postulation here is that node voltages are maintained between 0.95 and 1.05 pu. Transformer Tap-position limits:

$$T_k^{min} \le T_k \le T_k^{max\,i} \in N_T \quad (13)$$

For load flow analysis the value of T_k^{min} = 0.7, T_k^{min} = 0.1 and T_N = 3. The real and reactive power generation limits:

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \quad (14)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max\,i} \in N_G \quad (15)$$

Where:

P_{gi}^{min} = The minimum active power limits of generator at bus 'i'

P_{gi}^{max} = The maximum active power limits of generator at bus 'i'

Q_{gi}^{min} = The minimum reactive power limits of generator at bus 'i'

Q_{gi}^{max} = The maximum reactive power limits of generator at bus 'i'

The SVC device is limited by the maximum reactive power it can inject:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{Max} i \in N_C \quad (16)$$

Where:

Q_{ci}^{min} and Q_{ci}^{max} = The maximum and reactive power supplied by the SVC

N_C = The number of weak buses with SVC device

Transmission line power flow limit:

$$L_i \le L_i^{Max} i \in N_l \quad (17)$$

Where:

L_i^{max} = The maximum power flow in the bus 'i'

N_l = The number of buses

Firefly algorithm: Firefly Algorithm (FA) was first developed by XIN-She Yang in late 2007 and 2008 at Cambridge University which was based on the flashing patterns and behavior of fireflies (Xin-She, 2014). The working of FA is based on the following three idealized rules; all flies are unisexual; implication is that any fly can attract the other regardless of sex; the level of attraction is directly proportional to the intensity of light. The less bright fly is always attracted by the brighter one and it moves toward it. The brightness is based on the objective functions evaluated value. The basic elements of firefly technique are listed and defined as follows:

Attractiveness: In the Firefly algorithm, the form of attractiveness functions of a firefly is given by the following monotonically decreasing function:

$$\beta(r) = \beta_0 \times \exp\left(-\gamma r^m\right),\ m \geq 1 \qquad (18)$$

Where:

r = The distance between any two flies
γ = The absorption coefficient
β_0 = The initial attractiveness

Distance between fireflies: The distance between any two fireflies i and j at positions X_i and X_j, respectively, can be defined as:

$$r_{ij} = \left\|X_i - X_j\right\| = \sqrt{\left(\sum_{k=1}^{d} X_{i,j} - X_{j,k}\right)} \qquad (19)$$

Where:

$X_{i,k}$ = The kth component of the spatial coordinate
X_i = The ith firefly
d = The number of dimensions

Movement: The movement of a firefly 'i' which is attracted by a more attractive i.e., brighter firefly 'j' is given by:

$$V_{i(new)} = V_{i(old)} + \beta_0 \times \exp\left(-\gamma r_{ij}^2\right) (Xj - Xi) + \propto \left(\text{rand} \frac{1}{2}\right) \qquad (20)$$

Where, the first term refers to current position of a firefly, the second term is due to firefly's attractiveness to light intensity seen by adjacent fireflies and the third term is used to create random movement of a firefly. The coefficient α is a randomization parameter determined by the problem of interest, rand is a random number distributed in [0, 1]. The various steps involved and flow chart for solving the optimal facts allocation using FA is listed below.

Step1: Read the system data such as line data, load data, generator buses, sack bus and initial settings.

Step 2: Initialize the parameters and constants for Firefly algorithm. They are N, $\propto^{max}$,$\propto^{min}$, β_0, γ^{min}, γ^{max} and $iter^{max}$ (maximum number of iterations). Tolerance is set to 1E-6 and maximum number of iterations for load flow is taken as 1000.

Step 3: Using Eq. 18 and 19 find attraction and distance of the flies. Attractiveness is based the strength of the better solution the files with higher level of attraction observe other files with less level attraction.

Step 4: Move the flies to the new position using Eq. 20. Fitness values are calculated for the new positions of the fireflies. If the new fitness value is better than previous P_{best} value then P_{best} value for that firefly is modified to the new value. Similarly, G_{best} value identified from the latest P_{best} values is memorized.

Step 5: The process is stopped when terminating criteria is reached. The termination criteria used in this work is the specified maximum number of cycles. Otherwise go to step 3.

Step 6: The value of G_{best} gives the optimal SVC sizes in n candidate locations, the transformer tap position and generator bus voltages.

Step 7: Print bus voltages, line flows and total system losses.

RESULTS AND DISCUSSION

Minimization of fuel cost: The results were obtained for modified IEEE 30 bus test system which includes windfarm at bus No. 22. The windfarm consists of 20×2 identical wind generators and parameters are taken from (Jabr and Pal, 2009; Chen *et al*., 2005). Load data and thermal generator cost details are available in Alsac and Scott (1974). The loads remain constant for the scheduling period and the generations do not depend on previous schedules. So, this is known as static OPF. Depends upon the values of penalty costs Pc_{ov} and Pc_{un}, the contribution of windfarm and thermal generators to meet the load demand varies. For demonstration the values of Pc_{ov} and Pc_{un} are chosen as Pc_{un} = 2\$ Mwh^{-1} and PC_{ov} = 5\$ Mwh^{-1}. The results obtained by means of FA approach were compared with those obtained by means of Modified Cuckoo Search (MCS) and Modified Particle Swarm Optimization (MPSO). The results obtained by proposed FA method and MCS,MPSO methods have been tabulated in Table 1-6. Analysis of this case study proved the fact that Firefly algorithm provided much better results compared to MCS, MPSO methods in terms of loss reduction, cost and computational time. Firefly algorithm produced optimal solution in lesser iterations.

Modified PSO: There are some modified PSO discussed here:

- $C_1 = C_2 = 2$
- Population size =30
- Maximum number of iterations ($iter^{max}$) = 500 Mutation probability
- $P_m = 0.1$

Firefly algorithm: The firefly parameters selected after several test runs is as follows:

- No. of flies = 30
- α = 0.2
- β = 1.0
- γ = 1.0 Maximum number of iterations ($iter^{max}$) = 500

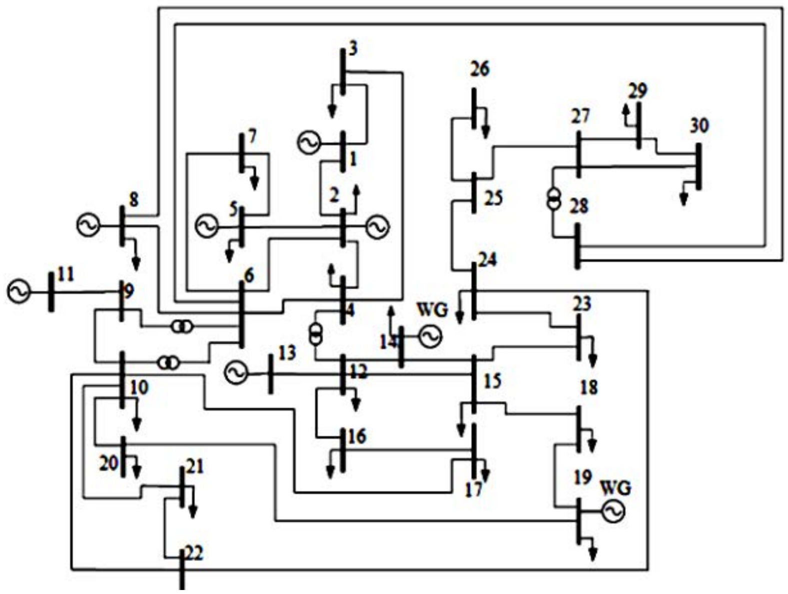

Fig. 2: Modified IEEE 30 bus power system

Table 1: Comparison of solution with Firefly algorithm for IEEE 30 bus system (PC_{un} = 2\$ MWh^{-1}, PC_{ov} = 5\$ MWh^{-1}) generator data

	Voltage (pu)			P_g (MW)			Q_g (MVAR)		
Bus No.	FA	MCS	MPSO	FA	MCS	MPSO	FA	MCS	MPSO
1	1.1000	1.1000	1.1000	154.8031	155.7057	159.8840	-15.2031	-15.2067	-15.3655
2	1.0889	1.0886	1.0882	43.4986	43.5298	44.5701	20.3634	20.5133	23.2082
5	1.0632	1.0629	1.0606	19.7532	19.6225	15.0000	27.1432	27.2278	29.2380
8	1.0743	1.0731	1.0686	10.0000	10.0000	10.0000	39.0634	39.1538	39.9999
11	1.1000	1.1000	1.1000	10.0000	10.0000	10.0000	6.6413	6.7508	4.6956
13	1.1000	1.1000	1.0828	12.0000	12.0000	12.0000	19.8632	19.7784	24.0000
22 (wind)	1.0675	1.0632	1.0571	40.0000	40.0000	40.0000	-20.4326	-20.4110	-20.3607

Table 2: Shunt capacitor value (Optimized values in FF only)

Bus No.	FA	MCS	MPSO
10	19	19	19
24	2	5	1

Table 3: Transformer tap setting

	Transformer tap setting		
Line connecting	FA	MCS	MPSO
6-9	0.96	0.9750	0.95
6-10	0.95	0.9500	0.95
4-12	1.00	1.0000	1.05
28-27	0.96	0.9750	0.95

Minimization of active power loss and voltage deviation: To find the effectiveness and efficiency of the proposed Firefly algorithm based reactive power optimization approach, the modified IEEE 30 bus power system is used as the test system. The Firefly algorithm has been implemented in MATLAB programming language. The standard IEEE 30 bus system consists of 6 conventional thermal generators at buses 1, 2, 5,8,11 and 13. It has 41 branches and 21 load buses. All branch datas are taken from references (Alsac and Scott, 1974; Yang *et al*., 2008).

Table 4: Optimisation results

Costs	FA	MCS	MPSO
Total cost (\$ h^{-1})	732.9631	733.2596	735.3632
Thermal cost(\$ h^{-1})	660.7342	660.7858	662.8894
Wind cost (\$ h^{-1})	72.4738	72.4738	72.4738
No. of iterations For convergence	285.0000	290.0000	288.0000
Computational time to convergence	33.5	34.58	343.20
Losses (MW)	7.43	7.46	8.05
Cost of SVC	-	-	-

For an actual transmission grid with windfarms connection, Niu and Xu (2012) provided a framework for quantitative analysis of optimal reactive power planning (Niu and Xu, 2012). According to that wind farms are connected to the grid at bus14 and bus19 and it is denoted as modified IEEE 30 bus system which is shown in Fig. 2.

Each wind farm consists of fifteen 800 KW wind turbines (nominal wind speed 12 m sec^{-1}) with the total installed capacity of 12MW. There are two assumptions used here which are stated as that there is a similar wind condition in the two areas and for all fifteen wind turbines

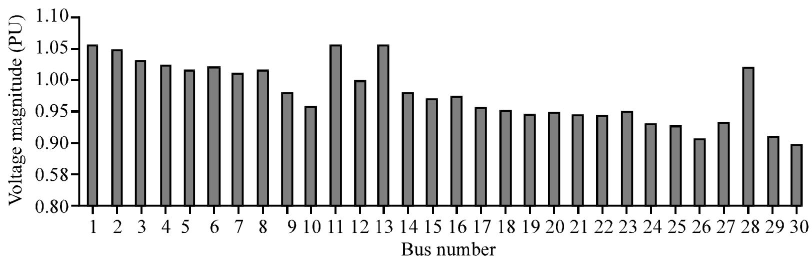

Fig. 3: Voltage profile for IEEE 30 bus system without wind

Table 5: The bus parameters recognize

Bus No.	3	4	6	7	9	10	12	14	15	16	17
FA	1.0806	1.0752	1.0754	1.0642	1.0932	1.0749	1.0756	1.0635	1.0597	1.0691	1.0682
MCS	1.0806	1.0753	1.0713	1.0606	1.0874	1.0749	1.0749	1.0616	1.0595	1.0682	1.0678
MPSO	1.0806	1.0753	1.0668	1.0571	1.0913	1.0702	1.0519	1.0405	1.0405	1.0527	1.0597

Table 6: Parameters are chosen

Bus No.	18	19	20	21	23	24	25	26	27	28	29	30
FA	1.0621	1.0578	1.0601	1.0645	1.0603	1.0532	1.0587	1.0365	1.0649	1.0732	1.0502	1.0461
MCS	1.0531	1.0524	1.0573	1.0626	1.0526	1.0516	1.0544	1.0373	1.0649	1.0703	1.0459	1.0349
MPSO	1.0390	1.0412	1.0477	1.0568	1.0375	1.0417	1.0566	1.0396	1.0748	1.0640	1.0560	1.0451

Table 7: Different levels of wind penetration in IEEE 30 bus system

Case No.	Wind speed (m sec^{-1})	Percentage of wind power penetration (%)	P_{wf}/MW	Q_{wf}/MVAR
Scenario 1	6.51	25.0	3.0	0.0
Scenario 2	7.56	37.5	4.5	-0.9
Scenario 3	8.21	50.0	6.0	-1.4
Scenario 4	9.12	62.5	7.5	-1.9
Scenario 5	9.96	75.0	9.0	-2.2
Scenario 6	11.13	87.5	10.5	-3.0

in a windfarm, same wind speeds are considered for a particular scenario. Output power produced by each wind turbine depends on the wind speed. Real power and reactive power produced by each windfarm for the mean value of wind speed in a particular scenario was obtained by monte-carlo simulation method and is tabulated. Simulation studies have been carried for different levels of wind penetration as shown in Table 7. Each scenario is characterized by wind penetration levels. In Table, P_{wf} and Q_{wf} represent the real and reactive power produced by each wind farm.

In this modified IEEE 30 bus system, the generator voltages, transformer tap settings and reactive power source installation are optimizable variables. System voltage profile for the base case of IEEE 30 bus system which is shown in Fig. 3 was obtained by conducting load flow for the initial operating point which is given in bus data table (Yang *et al*., 2008). From the analysis, it was found that there are violations in the lower limit of voltage at load buses 18.19, 20, 21, 22, 23, 24, 25, 26, 27, 29 and 30.

Therefore, dynamic reactive power compensation using FACTS controller is required to minimize the real power losses and to improve the voltage profile of the power system connected with wind power. The addition of SVC helps to improve the voltage profile of Weak buses. In order to maintain voltage profile at all buses within prescribed limits SVC can be connected to specific locations by susceptance based voltage sensitivity analysis method which is (Niu and Dong, 2012). For the modified IEEE 30 bus system, bus numbers 23, 26 and 29 have been identified as best SVC compensation buses for placement (Fig. 4).

Table 8 shows the optimized SVC ratings calculated by using Firefly algorithm in the modified IEEE 30 bus system for different scenarios. Optimal values for SVC setting are searched using Firefly algorithm and its capability is demonstrated by comparison between power losses of the system before and after compensation Fig. 5.

The firefly parameters selected after several test runs is as follows: Number of flies: 40; Maximum number of Iterations = 500; α = 0.2; β = 1.0; γ = 1.0.

After providing reactive power compensation by SVC, the voltages of all the buses in modified IEEE 30 bus power system are close to 1 pu. At the same time, there is significant reduction in real power loss which corresponds to annual savings of energy cost. The SVC compensation impact on the improvement of bus voltages are compared in Fig. 3 and 4. It was observed that high capacity of wind penetration has

Table 8: Optimal VAR injection and objective function results based on Firefly algorithm

	Scenarios					
SVC rating	1	2	3	4	5	6
Q1 (MVAr)	9.8605	13.0798	12.2273	11.5663	11.5067	11.8900
Q2 (MVAr)	29.7100	32.5477	4.7143	20.0958	13.0295	24.4896
Q3 (MVAr)	11.9362	10.5295	10.2649	10.5339	10.5245	10.2819
Power loss without compensation (pu)	0.1719	0.1679	0.1644	0.1611	0.1574	0.1544
Power loss with SVC compensation (pu)	0.1538	0.1502	0.1461	0.1439	0.1406	0.1377
Reduction in power losses (pu)	0.0181	0.0177	0.0183	0.0172	0.0168	0.0167

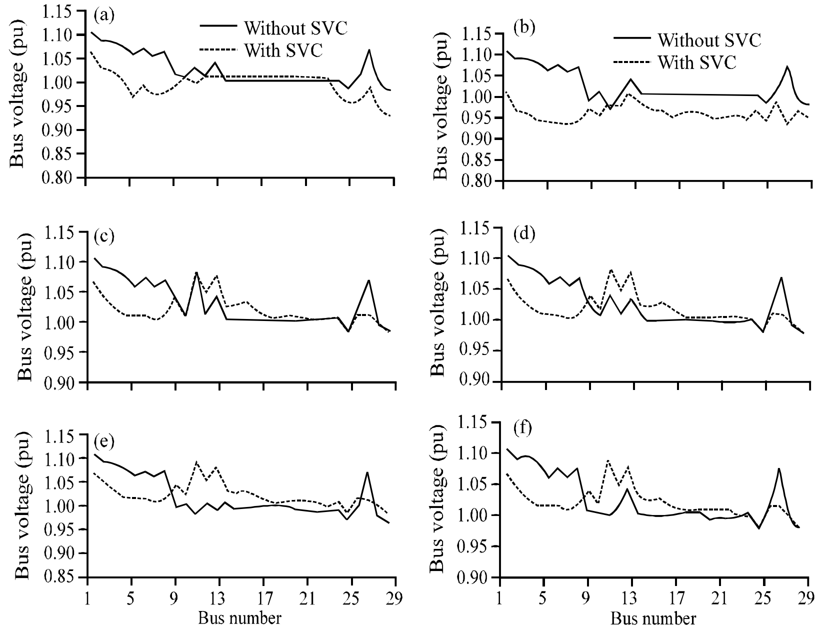

Fig. 4: IEEE 30 bus voltage profile with and without SVC (Scenarios 1-6)

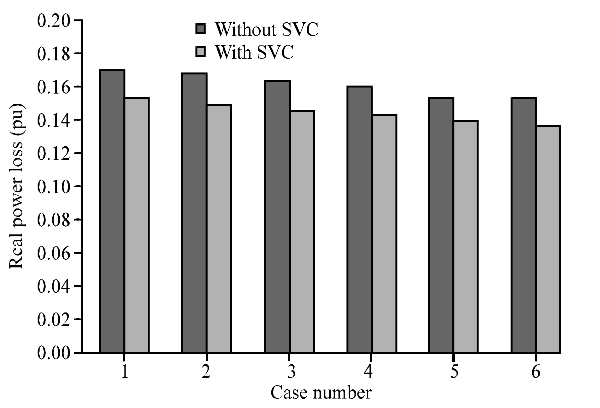

Fig. 5: Real power loss before and after SVC compensation

a severe effect on the voltage profile of the power system. However, this is based on the P, Q and slip of the DFIG (Doubly Fed Induction Generator). Operating the wind turbine with 70% penetration levels are optimal and reactive power consumption is also found to be less.

The results obtained by means of firefly approach were compared with those obtained by means of typical differential evolution algorithm in reference (Niu and Xu, 2012). Firely algorithm is superior to differential evolution method in terms of convergence results and reduced elapsed time.

The FA is based on attraction and attractiveness decreases with distance. Therefore, FA has two major advantages over other optimization algorithms: automatical subdivision and ability of dealing with multimodality. This results in the fact that the whole population can automatically subdivide into subgroups and each group can swarm around each mode or local optimum. Among all these modes, the best global solution can be found. Second, this subdivision allows the fireflies to be able to find all optima simultaneously if the population size is sufficiently higher than the number of modes. All these advantages make FA very unique and efficient for solving multi objective reactive power optimization problem.

CONCLUSION

The multi objective Optimal Power Flow (OPF) problem in power system comprised of wind farms has been analyzed and Firefly algorithm based solution methodology has been proposed in this study. The OPF problem has been formulated as a constrained optimization problem to minimize active power losses to improve the voltage profile and minimisation of fuel cost. The proposed approach has been tested in the modified IEEE 30 bus system with wind power penetration. The simulation result shows the efficacy of the Firefly algorithm to solve OPF problem. Results indicate that the real power loss has been greatly reduced and all bus voltages are within stability limit. It was found that the varying levels of wind penetration create severe voltage variations which may result in blackout. Electrical power system performs better when optimum reactive power compensation is carried out by SVC under varying wind power penetration scenarios. It can be concluded that Firefly algorithm is a promising technique for solving complex optimization problems in power systems.

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