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Optimal power flow in the Presence of wind power considering reserve cost/Penalty cost using particle swarm optimization

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Abstract- This study proposes a solution to the optimal power flow (OPF) in power systems incorporating wind power. The wind generated electricity's cost modeling is presented which owes to the stochastic nature of wind speed based on the Weibull probability density function. The wind associated costs comprise of (i) reserve cost arising out of overestimation of wind farm output and (ii) penalty cost for not using total available wind power which are included in the conventional OPF. Furthermore, the Q-V formulation of induction generator is deduced which is incorporated through a modification in the conventional load flow solution. A firefly algorithm optimization technique is employed and compared with particle swarm optimization for solving OPF with wind power involved. A modified IEEE 30-bus systems are used as test systems and it is observed that the firefly algorithm performs better than particle swarm optimization.

I INTRODUCTION

Wind power generatio0n is a kind of technology which transforms wind energy into electric power. Making use of wind energy to generate electricity can not only reduce the environmental pollution but also reduce the fuel cost of the power system, which brings the considerable economic benefits. At present, it tends to make large wind farms be connected to power grid. Because wind energy has become the least expensive source of new electric power that is also compatible with environment preservation programs, many countries promote wind power technology by means of national programs and market incentives.

Wind power expansion has been accelerating worldwide due to technological progress, cost reduction and concerns over global warming partly caused by greater concentration of CO_2 in the atmosphere. Power plants using coal, natural gas and oil have been contributing a large portion of the concentration. As a result, there has been growing interest in wind power production modeling and simulation studies.

Nowadays, increasing price of fossil fuels and energy production cost, in addition to increasing global concerns on environmental issues cause energy section to seek alternative. In this regard, Renewable Energy Sources (RESs) would be a good choice to replace fossil fuels. Among RESs, wind energy is the most famous energy source. So far, many countries have integrated wind power generation into their power systems. In spite of all good features with wind power, such as zero-emission and relatively low cost energy, using wind power may lead to several problems due to its intermittent, volatile nature i.e. power system's planners have to use complicated methods to operate power systems. It is obvious that wind power generation varies with wind speed variations. In other words, wind power is a function of wind speed. There are many solutions considered to compensate wind intermittency, such as Energy Storage Systems (ESSs) and also transacting power with adjacent power systems. Moreover, fast response generating units is one of the most effective ways to deal with wind power uncertainty.

The paper is organized as follows. Section II explains the PSO optimization technique. Section III describes the firefly algorithm optimization technique. The simulation and results are developed in Section IV. Finally, Section V presents the main conclusions.

II Particle Swarm Optimization Technique

A. Depiction of wind speed and wind generator input/output

The PDF for Weibull distribution is given by:

$$f_V(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{(k-1)} e^{\left(\frac{-v}{c}\right)^k},\ 0 < v < \infty \ldots(1)$$

Where *v* -wind speed (m/s)
c -scale factor
k- shape factor

below figure shows wind speed distribution

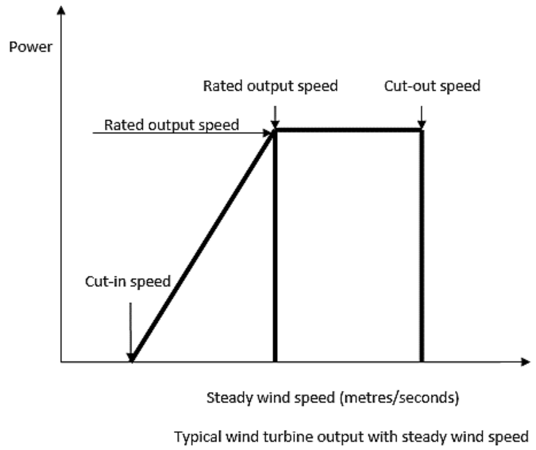


Fig :1 Wind Turbine Output with Steady wind Speed

The power curve has three key points on the velocity scale:
• Cut-in wind speed – the minimum wind speed at which the machine will deliver useful power.
• Rated wind speed – the wind speed at which rated power is obtained (rated power is generally the maximum power output of the electrical generator).
• Cut-out wind speed – the maximum wind speed at which the turbine is allowed to deliver power (usually limited by engineering loads and safety constraints).
Below the cut-in speed, of about 3 m/s, the wind turbine remains shutdown as the speed of the wind is too low for useful energy production. Then, once in operation, the power output increases following a broadly cubic relationship with wind speed until rated wind speed is reached. Above rated wind speed the The choice of cut-in, rated and cut-out wind speed is made by the wind turbine designer who, for typical wind conditions, will try to balance obtaining maximum energy extraction with controlling the mechanical loads (and hence the capital cost) of the turbine.

The power output of the WECS with a given wind speed input may be given as:

w= 0 ,for v< vi and v>vo..(2)

$w = w_r \left(\frac{v-vi}{vr-vi}\right)$, for vi ≤ v ≤ vr….(3)

w= w_r , for vr ≤ v ≤ vo…(4)

where,

w = WECS output power (typical units of kilowatt or megawatt)
w_r = WECS rated power;
V_i =cut-in wind speed (typical units of miles/hour or miles/second);
V_r = rated wind speed
V_o =cut-out wind speed

In WECS program, these formulas are used through a graphical procedure to estimate the power produce by adjustable limits.

Thus, it is seen that the WECS has: 1) no power output up to cut-in wind speed; 2) a linear power output relationship between cut-in and rated wind speed; 3) a constant rated power output between the rated wind speed and cut-out wind speed; and 4) once again has no power output with wind speeds greater than the cut-out wind speed.

Due to the fact that the WECS power output has a constant zero value below the cut-in wind speed and also above the cutout wind speed, and due to the fact that the power output is constant between rated wind speed and cut-out wind speed, the power output random variable will be discrete in these ranges of wind speed. The WECS power output is a mixed random variable, which is continuous between values of zero and rated power, and is discrete at values of zero and rated power output.

The Power output is zero for speed below the cut-in wind speed. In the interval of wind speed between the cut-in and rated speed, the maximum coefficient power can be obtained using the wind power equation. The output power remains at the maximum value for the wind speed in the interval between rated speed and cut-out speed, where the upper limit is cut-out point. For wind speed larger than cut-out point, for safety, no power is generated and therefore, remain zero.

B.Transformation from wind speed variable to wind power output variable

If wind speed is assumed to be come from weibull distribution, it is important to transform wind speed distribution to wind power distribution. As the wind power can be viewed as random variable, the output wind generation may be regarded as random variable through transformation.

Considering the statistical nature of wind speed, the transformation can be accomplished by below function:

$$f_w\ (W) = f_v\ \left(v(w)\right)\left(\frac{dv}{dw}\right) \ldots\ldots\ldots\ldots\ldots(5)$$

The probability of wind speed being smaller than cut in speed (i.e.v< v_i) and larger than cut-out speed (i.e. v > v_o) is expressed as follows: F_W (w=0) = 1- $\exp\left(-\left(\frac{v_i}{c}\right)^k\right)$+ $\exp\left(-\left(\frac{v_o}{c}\right)^k\right)$……(6)

The probability of wind speed between rated output speed and cut-out speed is given by :

$$F_w\,(\mathrm{w}=w_r) = \exp\left(-\left(\frac{v_r}{c}\right)^k\right) + \exp\left(-\left(\frac{v_o}{c}\right)^k\right) \ldots\ldots(7)$$

Above two equations are for discrete regions.

The probability of wind speed between cut in speed and rated output speed is obtained by substituting equation (3) in equation (5) and is expressed as :

$$f_w\,(\mathrm{w}) = \left(\frac{k\,(v_r - v_i)}{c w_r}\right) \left(\frac{v_i w_r + w(v_r - v_i)}{c w_r}\right)^{k-1}$$
$$\exp\left(\left(\frac{v_i w_r + w\,(v_r - v_i)}{c w_r}\right)^k\right) \ldots\ldots(8)$$

Above equation is for linear region.

The forecast of wind speed as well as wind power within a short time lag is more accurate and the variance of distribution is smaller than those forecasts conducted for a longer time lag.

As with any other mixed discrete and continuous probability function, the sum of the discrete probabilities at zero and rated power, plus the integral from 0 to 1 of the continuous function will sum to 1.

C. Introduction to PSO

There are many methods in optimization. They are mainly classified as classical methods and AI methods. Some classical methods are like linear programming, Non linear programming, Quadratic programming, Newton's method, Interior point method etc. It requires derivative of objective function.Artificial Intelligence (AI) Methods are like ANN,FL, PSO,ACO,DE etc.

PSO is an artificial intelligent optimization method. It was developed in 1995 by James Kennedy and Russell Eberhart. PSO is a fast, simple and efficient population-based optimization method.

It has been inspired from the social behavior of organisms such as bird flocking and fish schooling. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution

Each particle is treated as a point in a N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles.

This method works in same manner as birds fly. As birds roam in search of their food, in similar manner particles move for best solution. As the position of leader bird changes, every bird starts following it. Leader is a global best bird (particle). PSO is also known as Cooperative Movement.

Some basic terms used in PSO are:

- **Fitness function-** it is our objective function which we need to minimize.
- **Particle(bird)** – it is the initial guess, which gives us a possible solution.
- **Swarm** – it is the set of particles.
- P_{besti} **(personal best)**- best position of a particular particle (i^{th}particle)
- g_{best} **(global best)**- Best position of particle which gives minimum value of fitness function.

Every particle has two variables, position and velocity(step length)

Each particle updates its position based upon its own best position, global best position among particles and its previous velocity vector according to the following equations:

Equation for new position: new = old + step length

$$x_i^{k+1} = x_i^k + v_i^{k+1} \ldots\ldots\ldots\ldots\ldots(9)$$

Where,x_i^k -position of i^{th} particle at k^{th} iteration.

Similarly equation for velocity is given by :

V_i^{k+1} = w * v_i^k + c_1*r_1 * (p_{best_i} - x_i^k) + $c_2 * r_2$ * (g_{best} - x_i^k)…………..(10)

Where,

V_i^{k+1} - velocity of particle at (k+1)th iteration.

c_1, c_2 - positive constants having value 2.1 and 2 respectively.

r_1, r_2 - random numbers generated between [0, 1]

p_{best_i} - personal best position of i^{th} particle.

g_{best} -position of global best particle

W – inertia weight of particle

best particle

W – inertia weight of particle

III Firefly Algorithm

Optimization problem is one of the most challenging problems in the field of operation research. The goal of the optimization problem is to find the set of variables that results into the optimal value of the objective function, among all those values that satisfy the constraints. Many new types of optimization algorithms have been explored. One of them is a nature-inspired type. Algorithms of this type are such as an ant colony optimization (ACO) algorithm proposed by Marco Dorigo in 1992 which has been successfully applied to scheduling problems. ACO is inspired by the ants' social behavior of finding their food sources and the shortest paths to their colony, marked by their released pheromone .

Another example of this type of algorithms is a particle swarm optimization (PSO) algorithm developed by Kennedy and Eberhart in 1995. PSO is based on the swarming behavior of schools of fish and bird in nature. PSO has been successfully applied to a wind energy forecasting problem. where wind energy is estimated based on two meta-heuristic attributes of swarm intelligence.

A firefly algorithm is yet another example. It is a population-based algorithm inspired by the social behavior of fireflies . Fireflies communicate by flashing their light. Dimmer fireflies are attracted to brighter ones and move towards them to mate. FA is widely used to solve reliability and redundancy problems. A species of firefly called Lampyride also used pheromone to attract their mate.

Another well-known nature-inspired algorithm is genetic algorithm (GA). GA is inspired by the process of natural evolution. It starts with a population of chromosomes and effects changes by genetic operators. Three key genetic operators are crossover, mutation, and selection operators. Our algorithm proposed in this paper combines attributes of firefly mating and its pheromone dispersion by the wind with the genetic algorithm. GA is used as the core of our algorithm while the attributes mentioned are used to compose a new selection operator.

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 behaviour of
fireflies. In essence, FA uses the following three idealized rules:

[1] Fireflies are unisex so that one firefly will be attracted to other fireflies regardless of
their sex.

[2] The attractiveness is proportional to the brightness, and they both decrease as their
distance increases. Thus for any two flashing fireflies, the less brighter one will move
towards the brighter one. If there is no brighter one than a particular firefly, it will
move randomly.

[3] The brightness of a firefly is determined by the landscape of the objective function.

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies,
we can now define the variation of attractiveness β with the distance r by

$$\beta = \beta_0 e^{-\gamma r^2}$$

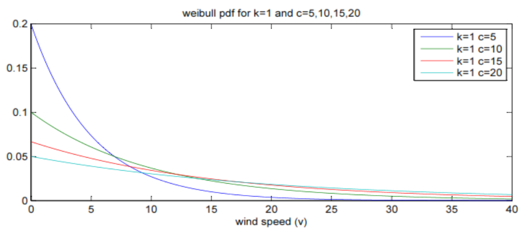
where β_0 is the attractiveness at r = 0.
The movement of a firefly i is attracted to another more attractive (brighter) firefly j is
determined by

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r^2_{ij}} \left(x_j^t - x_i^t\right) + \alpha_t \varepsilon_i^t,$$

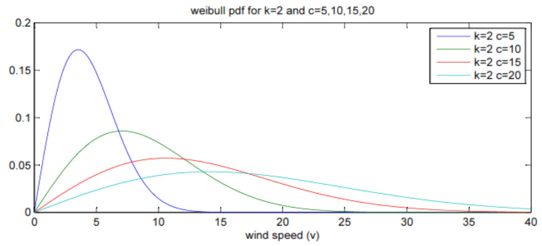
where the second term is due to the attraction. The third term is randomization with α_t being the randomization parameter, and ε_i^t is a vector of random numbers drawn from a Gaussian distribution or uniform distribution at time t. If β_0
= 0, it becomes a simple random walk. On the other hand, if γ = 0, it reduces to a variant of particle swarm optimi-sation. Furthermore, the randomization ε_i^t can easily be extended to other distributions such as L´evy flights. A demo version of firefly algorithm implementation by Xin-She Yang, without L´evy flights for simplicity, can be found at Mathworks file exchange web site.

IV.SIMULATION RESULTS

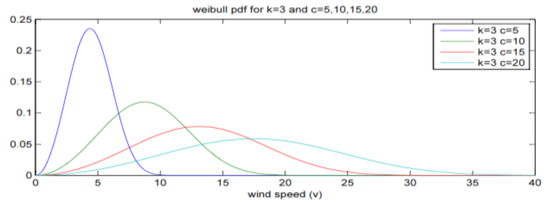
A. Particle swarm optimization



[Fig 2: Weibull probability density functions for k factor of 1 and c factors of 5, 10, 15, 20]



[Fig 3: Weibull probability density functions for k factor of 2 and c factors of 5, 10, 15, 20]



[Fig 4:Weibull probability density functions for k factor of 3 and c factors of 5, 10, 15, 20]

Table 1: Comparison of total wind generation cost

Total cost of wind generation given in paper	Total cost of wind generation after simulation
72$	72.4737$

Table 2: Comparison of total generation cost

Total generation cost given in paper	Total generation cost after simulation
733.2596 $/h	733.5139 $/h

Table 3:*Firefly algorithm*

Total generation cost using PSO	*Total generation cost using FFA*
733.5139 $/h	*730.5632 $/h*

V. CONCLUSION

The OPF problem incorporating wind farms has been discussed and a solution methodology has been proposed in this paper. The wind generator cost modeling is presented which comprises of costs associated with underestimation and overestimation of wind power. Also IEEE 30 bus system is used as a test system. On this test system Particle Swarm Optimization method is employed and observed that after optimization losses are reduced, before optimization losses are 13.05MW and after 7.473MW.

Now firefly algorithm optimization method is applied and compare with PSO and observed that total generation cost is decreased in PSO total generation cost is 733.5139$/h and in FFA it is 730.5632$/h and losses is also reduced.

VI. APPENDICES

A.- WECS data

Parameters	Value m/s
Vi	3
Vo	25
Vr	10.28

B.-Conventional generator data IEEE 30 bus

Bus number	P_g^{max} MW	P_g^{min} MW	α	β	γ
1	50	200	0.00375	2	0
2	20	80	0.0175	1.75	0
5	15	50	0.0625	1	0
8	10	35	0.00834	3.25	0
11	10	30	0.025	3	0
13	12	40	0.025	3	0

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