2011 International Conference on Electrical Engineering and Informatics
17-19 July 2011, Bandung, Indonesia

AI Based Economic Load Dispatch Incorporating Wind Power Penetration

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Abstract:
Economic Load Dispatch (ELD) is one of the most important problems to be solved in the operation and planning of a power system. **Its objective is to schedule the power generation properly in order to minimize the total operational cost. Renewable energy resources such as wind power have significant attention in recent years in power system field. It reduces fuel consumption and also benefits in curbing emission. But wind power penetration into conventional systems due to its intermittent nature has some implications like security concerns. Thus a reasonable trade off is required between system risk and operational cost. In this paper a bi-objective economic dispatch problem considering wind power penetration is formulated. A fuzzy membership function is used to represent the dispatch of wind power into the conventional system. A particle swarm optimization algorithm, Genetic algorithm and a bacteria-foraging technique are adopted to develop a dispatch scheme compromising both the economic and security requirements. The results of all these 3 proposed techniques are compared. Numerical analyses are reported based on a typical IEEE-30-bus with six-generator test power system to show the validity and applicability of the proposed approaches.**

Introduction

The term economic load dispatch (ELD) is referred as scheduling the power generation in appropriate manner to satisfy the load demand while minimizing the total operational cost. In recent years with the rapid development of world economy people have paid more attention to fuel consumption and environmental protection. As one of the most promising non pollution renewable energy resources wind power has given more consideration. Comparing with the conventional generators, wind generators has advantage of reducing the dependences on fossil fuels and transmission losses, enhancing the independence and flexibility of large power grids. Due to intermittency and unpredictability nature of wind power generators, system may incur security problems when the wind power penetration into the traditional system exceeds certain level. For example, the system stability may be lost if there is excessive wind fluctuations. Thus to achieve a trade off between risk level and running cost a suitable dispatch scheme for the power system is desired taking into account the impacts of wind power penetration. In this paper ELD is modelled as a bi-objective optimization problem minimizing both system risk level and operational cost simultaneously. To achieve this, a suitable effective optimization procedure is needed. For this different AI techniques of optimization procedure which are considered to be salient tool, capable of resolving highly non linear and complex optimization problems with extraordinary convergence performance. Also due to intermittent nature of wind power generation, we use fuzzy membership function to indicate the system security level in terms of wind power penetration and wind power cost. Linear and Quadratic functions are used to represent the dispatcher's attitude towards wind power penetration.

The paper is organized as follows. Section 2 represents wind power penetration model described by fuzzy membership functions. Section 3 represents the formulation of dispatch problem. Section 4 describes the PSO algorithm. Section 5 describes GA and its algorithm. Section 6 describes the Bactero foraging and its algorithm. The results and analysis are presented at the end and compared. Finally conclusions and future scope of works are drawn.

2. Wind power penetration formulation

Wind power integration is an important issue to address for achieving a reliable power system including wind power source. Because of the unpredictable and variable characteristics of wind power, its integration into the traditional thermal generation systems will incur the operator's concern on system security. Fuzzy definition regarding wind penetration is a viable way to represent the penetration level of the wind power, since it is usually difficult to determine the optimal wind power that should be integrated into the conventional power grids. As shown in Fig. 1, a fuzzy membership function μ regarding the wind penetration is defined to indicate the system security level. It can be mathematically expressed in the following form

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$$\mu = \begin{cases} 1, & W \le W(P_D)_{min} \\ \dfrac{W(P_D)_{max} - W}{W(P_D)_{max} - W(P_D)_{min}}, & W_{min} \le W \le W_{max} \\ 0, & W \ge W(P_D)_{max} \end{cases} \quad 2.1$$

where W is the wind power incorporated in economic dispatch; $W(PD)$min is the lower bound of wind power penetration, below which the system is deemed secure; $W(PD)$max is the upper bound of wind power penetration, above which the system is considered as insecure due to the wind perturbations. Both $W(PD)$min and $W(PD)$max are dependent on the total load demand in the power dispatch.

The above defined membership function can also be represented in terms of the operational cost for incorporating wind power:

$$\mu = \begin{cases} 1, & WC \le WC(P_D)_{min} \\ \dfrac{WC_{max} - WC}{WC_{max} - WC_{min}}, & WC_{min} \le WC \le WC_{max} \\ 0, & WC \ge WC(P_D)_{max} \end{cases} \quad 2.2$$

where WC is the running cost of wind power in the power dispatch; WC (PD)min is the lower bound cost for producing wind power, below which the system is seen as secure; $W(PD)$max is the upper bound cost for including wind power, above which the system is considered as insecure due to the wind intermittency. In a similar fashion, both WC (PD)min and WC (PD)max are dependent on the total load demand in the power dispatch. In this study, sensitivity studies are also carried out to illustrate the impact of different allowable ranges of wind power penetration as well as different running costs of wind power on the final solutions obtained.

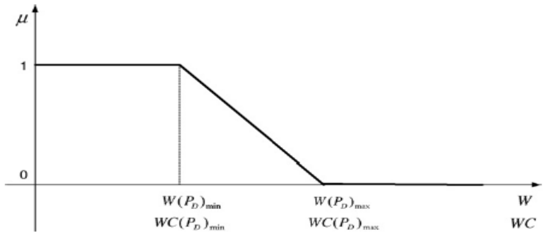

Fig. 1. Fuzzy linear representation of the security level in terms of wind penetration and wind power cost.

To reflect dispatcher's differing attitudes toward wind power penetration, a quadratic membership function is defined in (2.3). Note that here the attitude of a dispatcher refers to a corporate strategic or tactical plan that views wind power penetration with a pessimistic or optimistic attitude.

$$\mu = \begin{cases} 1, & W \le W(P_D)_{min} \\ a_w W^2 + b_w W + c_w, & W_{min} \le W \le W_{max} \\ 0, & W \ge W(P_D)_{max} \end{cases}$$

2.3

where a_w, b_w, and c_w are the coefficients of the quadratic function, which determine its curve shape reflecting the dispatcher's attitude toward wind power. As shown in Fig. 2, by selecting different coefficients a_w, b_w, and c_w, different curve shapes of the quadratic function can be defined. For the identical security level $\mu 0$, the penetration levels of wind power differ for different defined functions $w1 < w2 < w3$. The curves corresponding to these three values reflect the pessimistic, neutral, and optimistic attitudes of the dispatcher toward the wind power integration, respectively.

In a similar fashion, the security level can also be defined in terms of the operational cost of wind power.

$$\mu = \begin{cases} 1, & WC \le WC(P_D)_{min} \\ a_c WC^2 + b_c WC + c_c, & WC_{min} < WC < WC_{max} \\ 0, & WC \ge WC(P_D)_{max} \end{cases} \quad 2.4$$

where a_c, b_c, and c_c determine the curve shape of the quadratic function defined in terms of the running cost of wind power.

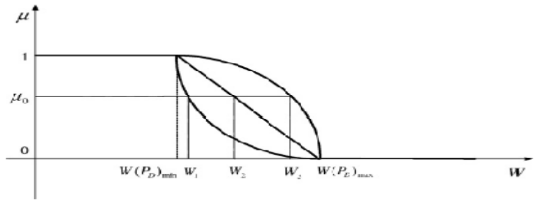

Fig.2. Fuzzy quadratic representation of the security level in terms of wind power penetration.

3. Dispatch Problem Formulation:

The dispatch model in the simulation uses centralized dispatch in a deregulated power system. Generators in the systems are thermal, wind. Constraints included in the calculation are the maximum and minimum values of generator output, the ramp rate of the generators, and reserve requirements. For simplification, transmission losses are neglected. The economic dispatch process aims at cost minimization subject to these constraints. The problem of economic power dispatch with wind penetration consideration can be formulated as a bi-criteria optimization model. The two conflicting objectives, i.e., total operational cost and system risk level, should be minimized simultaneously while fulfilling certain system constraints. This bi-objective optimization problem is formulated mathematically in this section.

3.1. Problem Objectives

There are two objectives that should be minimized simultaneously, that is, system risk level and the total operational cost.

Objective 1: Minimization Of System Risk Level

From the security level function defined in (2.1)–(2.2), we Know that the larger the value of membership function μ is, the more secure the system will become. If the wind penetration is restricted under a certain level, the system can be considered as secure. On the contrary, if excessive wind penetration is introduced into the power dispatch, the system may become insecure. Here we define an objective function which should be minimized in order to ensure system security:

$$R(\mu) = \frac{1}{\mu} \qquad 3.1$$

Objective 2: Minimization Of Operational Cost.

The cost curves of different generators are represented by quadratic functions with sine components. The superimposed sine components represent the rippling effects produced by the steam admission valve openings. The total \$/h fuel cost FC (PG) can be represented as follows:

$$\mathrm{FC}(P_G) = \sum_{i=1}^{M} a_i + b_i P_{\mathrm{Gi}} + c_i P_{\mathrm{Gi}}^2 \qquad 3.2$$

Where M is the number of generators committed to the operating system, ai, bi, ci, are the cost coefficients of the i-th generator, and PGi is the real power output of the i-th generator.P_G is the vector of real power outputs of generators and defined as

PG = [PG1, PG2, . . . , PGM]

The running cost of wind power can be represented in terms of the value of membership function μ which indicates the system security level. For the linear membership function case,

$$\mathrm{WC}(P_G, \mu) = C_{\mathrm{w}}(W_{\mathrm{av}} - (P_{\mathrm{D}} + P_{\mathrm{L}} - \sum_{i}^{M} P_{\mathrm{Gi}})) - \mu * \Delta\mathrm{WC} + \mathrm{WC}_{\max} \qquad 3.3$$

where *W*av is the available wind power from the wind farm, *C*w the coefficient of penalty cost for not using all the available wind power, *P*D the load demand, and *P*L is the transmission loss, and

$$\Delta\mathrm{WC} = \mathrm{WC}_{\max} - \mathrm{WC}_{\min}.$$

For the quadratic membership function case,

$$\mathrm{WC}(P_G, \mu) = C_{\mathrm{w}}(W_{\mathrm{av}} - (P_{\mathrm{D}} + P_{\mathrm{L}} - \sum_{i}^{M} P_{\mathrm{Gi}})) - \frac{b_c}{2a_c} \pm \sqrt{\frac{\mu - (c_c - ((b_c^2)/(4a_c)))}{a_c}} \qquad 3.4$$

The sign of the last term is determined by the curve shape of the defined quadratic function.

Thus, the total operational cost TOC can be calculated as

$$\mathrm{TOC}(P_G, \mu) = \mathrm{FC}(P_G) + \mathrm{WC}(P_G, \mu) \qquad 3.5$$

3.2. Problem Constraints

Due to the physical or operational limits in practical systems, there is a set of constraints that should be satisfied throughout the system operations for a feasible solution.

Constraint 1: Generation Capacity Constraint

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$\mathrm{Pmin} \leq \mathrm{PGi} \leq \mathrm{Pmax} \qquad 3.6$$

where Pmin Gi and Pmax Gi are the minimum and maximum power from generator i, respectively.

Constraint 2: Power Balance Constraint

The total power generation and the wind power must cover the total demand PD and the real power loss in transmission lines PL. For the linear membership function, this relation can be represented by

$$\sum_{i=1}^{M} P_{\mathrm{Gi}} + W_{\max} - \mu * \Delta W = P_{\mathrm{D}} + P_{\mathrm{L}} \qquad 3.7$$

For the quadratic membership function, the relation can be expressed by

$$\sum_{i=1}^{M} P_{\mathrm{Gi}} - \frac{b_{\mathrm{w}}}{2a_{\mathrm{w}}} \pm \sqrt{\frac{\mu \quad (c_{\mathrm{w}} \quad ((b_{\mathrm{w}}^2)/(4a_{\mathrm{w}})))}{a_{\mathrm{w}}}} = P_{\mathrm{D}} + P_{\mathrm{L}}$$

3.8The sign of the last term in (3.8) is determined by the curve shape of the defined quadratic function.

The transmission losses can be calculated based on the Kron's loss formula as follows:

$$P_{\mathrm{L}} = \sum_{i=1}^{M}\sum_{j=1}^{M} P_{\mathrm{Gi}} B_{ij} P_{\mathrm{Gj}} + \sum_{i=1}^{M} B_{0i} P_{\mathrm{Gi}} + B_{00} \qquad 3.9$$

where Bij , B0i, B00 are the transmission network power loss B-coefficients. It should be noted that the transfer loss of the wind power is not considered in this study.

Constraint 3: Available Wind Power Constraint

The wind power used for dispatch should not exceed the available wind power from the wind park:

$$0 \leq P_{\mathrm{D}} + P_{\mathrm{L}} - \sum_{i}^{M} P_{\mathrm{Gi}} \leq W_{\mathrm{av}} \qquad 3.10$$

Constraint 4: Security level constraint

From the definition of membership function shown from (2.1) to (2.4), the values of μ should be within the interval of [0, 1]:

$$0 \leq \mu \leq 1 \qquad 3.11$$

4. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr.Ebehart and Dr. Kennedy in 1995, inspired by social behaviour of bird flocking or fish schooling. PSO is a population based search method i.e. it moves from a set of points with likely improvement in every iteration. PSO uses a population of solutions called particles, which fly through the search space with directed velocity vectors to find a better solution. Each particle keeps track of its co –ordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This fitness value is stored. This value is called the pbest (personal best).Another 'best' value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the immediate neighbourhood of the particle. This location is called lbest (local best). When a particle takes all the population as its topological neighbours, the best value is called the gbest (global best).PSO concept consists of at each time step changing the velocity(accelerating) of each particle towards its pbest and lbest locations. Acceleration is weighted by a random term with separate random numbers being generated for acceleration towards pbest and lbest locations.

The velocity of the particle is given by

$$V_i^{(u+1)} = w * V_i^{(u)} + C_1 * \mathrm{rand}() * \left(\mathrm{pbest}_i - P_i^{(u)}\right) + C_2 * \mathrm{rand}() * \left(\mathrm{gbest}_i - P_i^{(u)}\right)$$

And the position is given by

$$P_i^{(u+1)} = P_i^{(u)} + V_i^{(u+1)}$$

The term $\mathrm{rand}() * \left(\mathrm{pbest}_i - P_i^{(u)}\right)$ is called particle memory influence. The term $\mathrm{rand}() * \left(\mathrm{gbest}_i - P_i^{(u)}\right)$ is called swarm influence. $V_i^{(u)}$ which is the velocity of i^{th} particle at iteration 'u' must lie in the range

$$V_{min} \leq V_i(u) \leq V_{max}$$

The parameter Vmax determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If Vmax is too high, particles may fly past good solutions. If Vmin is too small, particles may not explore sufficiently beyond local solutions. Vmax is often set at 10-20% of the dynamic range on each dimension. The constants C1and C2 pull each particle towards pbest and gbest positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions. The acceleration constants C1 and C2 are often set to be 2.0 .Suitable selection of inertia weight 'ω' provides a balance between global and local explorations Thus requiring less iteration on average to find a sufficiently optimal solution. The inertia weight w is set according to the following equation

$$W = W_{max} - \left[\frac{W_{max} - W_{min}}{ITER_{max}}\right] \times ITER$$

Where w -is the inertia weighting factor

Wmax - maximum value of weighting factor

Wmin - minimum value of weighting factor

ITERmax - maximum number of iterations

ITER - current number of iteration

The flowchart describing the procedure of Particle swarm optimization is shown below

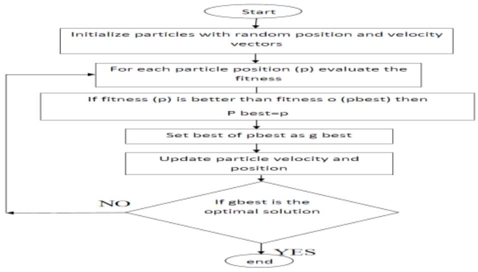

Fig.3 flowchart for PSO

4.2 Proposed algorithm steps:

The sequential steps to find the optimum solution

Step 1: The power of each unit, velocity of particles, is randomly generated which must be in the maximum and minimum limit. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2: Each set of solution in the space should satisfy

$$\sum_{i=1}^{N} P_{gi} = P_D + P_L$$

Where PL=Pgg*Bu*Pgg'+B0*Pgg'+B00u

Step 3: The cost function of each individual Pgi, is calculated in the population using the evaluation function F. Here F is

$$F = a \times (P_{gi})^2 + b \times P_{gi} + c$$

Where a, b, c are constants.

The present value is set as the **pbest** value.

Step 4: Each pbest values are compared with the other pbest values in the population. The best evaluation value among the pbest is denoted as **gbest**.

Step 5: The member velocity v of each individual Pg is updated according to the velocity update equation

Step6: The velocity components constraint occurring in the limits from the following conditions are checked

Vdmin = -0.5*Pmin

Vd**max = +0.5*Pmax**

Step 7: The position of each individual Pg is modified according to the position update equation

Pgid(u+1) = Pgid(u) + Vid(u+1)

Step 8: The cost function of each new is calculated If the evaluation value of each individual is better than previous pbest; the current value is set to be pbes**t.** If the **best pbest** is better than **gbest,** the value is set to be **gbest**

Step 9: If the number of iterations reaches the maximum, then go to step 10.Otherwise, go to step 2.

Step 10: The individual that generates the latest **gbest is the optimal generation power of each unit with** the minimum total generation cost.

5 Genetic Algorithm

Genetic algorithms are stochastic search techniques based on the mechanism of natural selection and survival of the fittest. Further, they exchange information among solutions to arrive at global optimum. More importantly, GAs appears attractive because of their superior robust behavior in nonlinear environment compared to other optimization techniques. The architecture of GA implementation can be divided into three phases namely:

1) Initial population generation,
2) Fitness evaluation and
3) Genetic operations.

GA optimization process is binary encoding which concerns the specification of the number of bits of each string to simulate the genes of an individual chromosome in which, the key computational tasks of GA are briefly highlighted.

The GA controls parameters, such as

1) Population size,
2) Crossover and
3) Mutation.

Probabilities of these parameters are selected, and an initial population of binary strings of finite length is randomly generated. Each of these individuals, comprising a number of chromosomes, represents a feasible solution to the search problem. The strings are then decoded back into their control variables to assess their fitness. If a pre-defined convergence criterion is not satisfied, then the genetic operations comprising selection and reproduction, crossover and mutation are carried out.

Fundamentally, the selection and reproduction mechanism attempts to apply pressure upon the population in a manner similar to that of natural selection found in biological systems.

A new population is created with poorer performing individuals eliminated while the most highly fit members in a population are selected to pass on information to the next generation. The widely used selection strategies are stochastic tournament and roulette wheel selection.

Conceptually, pairs of individuals are chosen at random from the population and the most fit of each pair is allowed to mate. Each pair of mates creates a child having some mix of the two parents' characteristics according to the crossover method. The process of randomly selecting pairs and mating the stronger individuals continues until a new generation of the same number of individuals is reproduced.

The crossover previously mentioned is the kernel of genetic operations. It promotes the exploration of new regions in the search space using randomized mechanism of exchanging information between strings.

The other work considered is the mutation process of randomly changing encoded bit information for a newly created population individual. Mutation is generally considered as a secondary operator to extend the search space and cause escape from a local optimum when used along with the selection and crossover schemes.

Due to the probabilistic nature of the generation process, the possibility exists that the genetic operations may destroy the highest fit individual. The elitist strategy ensures that the fittest individual generated actually is reproduced in the subsequent generation. Elitism can rapidly increase the GA performance by using the best solution as a seed for further optimization thus accelerating its convergence speed to global optimum.

5.1 Mechanism of GA optimization:

GA is a global search algorithm based on biological concepts which mimics the mechanics of nature and natural genetics. Compared to traditional methods, GA has several differences, such as:

1) The GA searches many candidate solutions in parallel, not a single point.
2) The GA uses probabilistic transition rules using GA operators rather than deterministic ones.
3) The GA does not require other auxiliary knowledge, except objective or fitness functions.
4) An attractive property of GA is the high probability of finding a global optimum.

5.2 Algorithm Steps:

The main steps involved in this optimization procedure are mentioned below as follows;

Step 1: Initialization process In this step all the global, generating unit parameters are initialized.

Step 2: GA Initial process In this step all the genetic parameters like, Chromosome length, Population size, Convergence, Number of iterations, Crossover, and Mutation probabilities are initialized.

Step 3: GA solving process In this step GA solving procedure is done like, Evaluating the Fitness value for each Chromosome, Genetic evolution using selection method and GA Operator, Production of Offspring population, etc.

Step 4: Convergence checking In this step the Convergence criterion is checked, if it is satisfied result is produced, else it goes to step 3 for further calculations.

6. BACTERIAL FORAGING:-

Foraging strategy is governed by following four steps:-

a) Chemo taxis
b) Swarming
c) Reproduction
d) Elimination or Dispersal

A) Chemo taxis:-

The motion patterns that the bacteria will generate in the presence of chemical attraction and repulsion are called Chemo taxes.

$\Theta i(j+1,k,l)=\theta i(j,k,l)+C(i)[\Delta i/\sqrt{(\Delta t + \Delta i)})$

Where

C(i)= The step size

Δi= Is a random vector

B) **Swarming:-**

Healthy bacteria try to attract other bacteria so that they will reach the desire location.

C) **Reproduction:-**

Bacteria have sufficient nutrients will reproduce and the least healthy will die.

The population is halved and so that the least healthy half dies and each bacterium in the other healthiest one splits into two and take the same position

$Sr = \frac{S}{2}$

D) **Elimination and dispersal: -**

The bacteria in the region are killed or a group is dispersed into a new part of the environment

From the voluntary point of view this was used to guarantees diversity of individuals and to strengthen the ability of global optimization.

6.1 ALGORITHM (BFO BASED ON PARTICLE SWARM OPTIMIZATION)

[step1] Initialization:

- Ped : Dimension of search space
- S : number of bacteria in population
- Ne : Chemo tactic step
- Ns :Swimming length
- Nre: Number of reproduction step
- Ned: Number of elimination Steps
- Ped : Elimination and dispersal step
- C(i) (i=1,2,3....,S) : Size of the step taken In random direction
- P(j,k,l) : P(j,k,l)= | θi(j,k,l) | ,i=1,2..S
- Generate a random vector φ(j) which lies in [-1,1]
- C1,C2,R1,R2,w :PSO parameters

[step2] Elimination Dispersal Loop: l=l+1.

[step3] Reproduction loop : k=k+1.

[step4] Chemo taxis loop: j=j+1.

[4.1] Take chemo taxis step for every bacterium(i).

[4.2] Compute fitness function: J(i,j,k,l) let Jlast= J(i,j,k,l)

[4.3] Tumble : let φ(j+1)=w*φ(j)+C1*R1*(Plbest-Pcurrent) + C2*R2*(Pgbest-Pgcurrent)

[4.4] Move: Let θi(j+1,k,l)=θi(j,k,l)+C(i)φ(j)

Compute fitness function=J(i,j,k,l)

Then Let J(i,j+1,k,l) = J(i,j+1,k,l) + Jcc (θ`(j+1,k,l), P(j+1,k,l)

[4.5] Swim : Let m=0;

While(m<Ns)

- Let m=m+1;
- If J(i,j,k,l)<Jlast
  Let Jlast= J(i,j,k,l)
  Let θi(j+1,k,l)=θi(j,k,)+C(i)φ(j)
  Compute fitness function : J(i,j,k,l)
  Let J(i,j+1,k,l)= J(i,j,k,l)+ Jcc(θ`(j+1,k,l),P(j+1,k,l)
- Else let m=Ns.

[4.6] Go to next bacterium

[Step5] If (j <Nc), go to Step 4.

[Step6] Reproduction: Compute the health of the bacterium i:

$J^i\text{health}=\sum_{j=1}^{Nc+1} J(i,j,k,l)$

Sort bacteria in the ascending order of health

[Step7] If (k<Nre), go to step 3

[Step8] Elimination and Dispersal: Eliminate and dispersal with probability Ped

[Step9] If (l<Ned),go to step 2

Test System

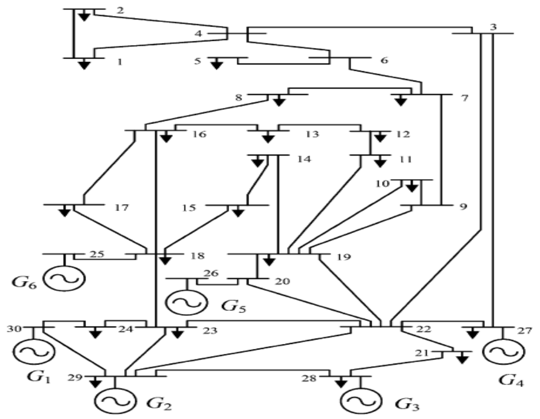

Fig. 4. IEEE 30-bus test power system.

Results Of PSO Technique

TABLE 1: COMPARISON OF COST, RISK LEVEL AND OPTIMAL GENERATOR SCHEDULING FOR THE TEST SYSTEM IEEE-30-BUS SYSTEM WITH WIND PENETRATION USING PSO IN DIFFERENT APPROACHES

Generators PGi and wind(MW)	Optimistic approach	Linear approach	Pessimistic approach
PG1	14.1726	22.0359	10.4900
PG2	26.6400	40.6675	31.7313
PG3	30.5391	26.3411	56.9413
PG4	77.3328	77.9386	83.2956
PG5	47.2077	38.3084	35.6357
PG6	35.1262	29.3872	16.2836
Wind	50.5235	51.3700	52.4156
Total operational Cost ($/hr)	788.9814	793.2459	799.1754
Risk level	5.4960	5.8769	6.1961

Quadratic representation (optimistic design): $a_w = -9.9607$, $b_w = 4.94$, $c_w = 0.4$.
Linear representation (neutral design): Wmin=0.2834, Wmax=0.5668.
Quadratic representation (pessimistic design): $a_w = 4.9803$, $b_w = -7.7629$, $c_w = 2.8$.
Penalty cost C_w is set 20 $/p.u

Results Of GA Technique

GA technique has been implemented with binary decoding method with single point crossover having crossover probability and mutation probability of 1 and 0.01 respectively performed with a population size of 80 having a chromosome size of 8 bit length.

TABLE 2: COMPARISON OF COST, RISK LEVEL AND OPTIMAL GENERATOR SCHEDULING FOR THE TEST SYSTEM IEEE-30-BUS SYSTEM WITH WIND PENETRATION USING GA IN DIFFERENT APPROACHES

Generators PG_i and wind (MW)	Optimistic approach	Linear approach	Pessimistic approach
PG1	14.1726	22.0359	11.4900
PG2	26.6400	40.6675	32.7313
PG3	30.5391	26.3411	56.9413
PG4	77.3328	77.9386	83.2956
PG5	47.2077	38.3084	35.6357
PG6	35.1262	28.3872	17.2836
Wind	51.5235	50.3700	49.4156
Total operational Cost ($/hr)	795.771	799.535	801.632
Risk level	5.5862	5.8665	5.9861

Results Of BFO+PSO Technique

The Parameter Setting Of BFO technique is considered as follows
The number of bacteria = 30
Number of chemo tactic steps = 30
Limits of the length of a swim = 4
The number of reproduction steps =8
The number of elimination-dispersal events = 2
Number of bacteria reproductions(splits) per generatio = s/2
The probability that each bacteria will be eliminated/dispersed = 25

TABLE 3: COMPARISON OF COST, RISK LEVEL AND OPTIMAL GENERATOR SCHEDULING FOR THE TEST SYSTEM IEEE-30-BUS SYSTEM WITH WIND PENETRATION USING BFO+PSO IN DIFFERENT APPROACHES

Generators PG_i and wind (MW)	Optimistic approach	Linear approach	Pessimistic approach
PG1	15.1726	22.0659	10.7900
PG2	28.3400	41.6675	30.9113
PG3	31.3391	25.3411	55.8113
PG4	76.2128	76.6386	82.1656
PG5	46.1077	37.1084	34.4157
PG6	34.1262	29.0372	17.2136
Wind	51.6135	52.4700	53.1156
Total operational Cost ($/hr)	783.971	787.535	790.632
Risk level	5.4862	5.6665	5.7861

TABLE 4: COMPARISON BETWEEN BFO AND BFO WITH PSO

Parameter	BFO	Proposed BFO with PSO
Velocity	Random(BFO)	Random(BFO) + PSO directed
Swarming effect	Yes	Yes
Attractant	Yes	Yes
Repellent	Yes	Yes
Unit vector	Yes	Yes
Step length	Yes (fixed)	Yes (variable)
Swimming in same direction	Yes	Yes
Simulation time (sec)	92	15

Conclusion

This work investigates the integration of wind power into conventional power networks and its impact on generation resource management. Wind power is environmentally friendly since it is able reduce the fossil fuel and natural gas consumption. Also, wind power needs less operational cost since it does not consume fossil fuels and natural gases. However, due to the intermittent and variable nature of the wind power, it is usually quite difficult to determine how much wind power should be integrated to ensure both power system security and operational cost reduction. In this paper, fuzzy representations of system security in terms of wind power penetration level and operational costs are adopted in constructing economic dispatch models. Different design scenarios can be formulated according to dispatcher's attitudes toward wind power integration with respect to risk and cost.out of the three proposed techniques bacteria foraginf technique combined with PSO is found to give better optimal solution at lower operational cost. It can also be implemented easily

This finally leads to an outline of the future directions for research and development efforts in this area. In PSO method selection of parameters are important. So, the parameters may be optimized by using the ANN method. Any other method can be applied with PSO to improve the performance of the PSO method. This work may be extended for new optimization techniques, like Artificial Immune Systems (AIS). This may be used to compare and find out the better optimization technique.

References

[1] E.A. DeMeo, W. Grant, M.R. Milligan, M.J. Schuerger, Wind plant integration: costs, status, and issues, IEEE Power Energy Magazine, November/December, 2005, pp. 38–46.
[2] J. Douglas, Putting wind on the grid, EPRI J., Spring 2006, 6–15.
[3] P.B. Eriksen, T. Ackermann, H. Abildgaard, P. Smith, W. Winter, R. Garcia, System operation with high wind penetration, IEEE Power Energy Magazine, November/December, 2005, pp. 65–74.
[4] Z.-L. Gaing, Particle swarm optimization to solving the economic dispatch considering the generator constraints, IEEE Trans. Power Syst. 18 (3) (2003) 1187–1195.
[5] P.K. Hota, S.K. Dash, Multiobjective generation dispatch through a neurofuzzy technique, Elect. Power Comp. Syst. 32 (2004) 1191–1206.
[6] T. Jayabarathi, K. Jayabarathi, D.N. Jeyakumar,Evolutionary programming techniques for different kinds of economic dispatch problems, Elect. Power Syst. Res. 73 (2005) 169–176.
[7] N. Jenkins, Embedded Generation IEE Power and Energy Series 31, The Institution of Electrical Engineers, 2000.
[8] J.Kennedy,R. Eberhart, Particle swarm optimization, in: IEEE Proceedings of the International Conference on Neural Networks, Perth, Australia, 1995, pp. 1942–1948.
[9] J. Kennedy, R. Eberhart, Swarm Intelligence, Morgan Kaufmann Publishers, San Francisco, 2001.
[10] K.Y. Lee, A.S. Yome, J.H. Park, Adaptive Hopfield neural networks for economic load dispatch, IEEE Trans. Power Syst. 13 (2) (1998) 519–526.
[11] V. Miranda, P.S. Hang, Economic dispatch model with fuzzy constraints and attitudes of dispatchers, IEEE Trans. Power Syst. 20 (4) (2005) 2143–2145.
[12] R. Piwko, D. Osborn, R. Gramlich, G. Jordan, D. Hawkins, K. Porter, Wind energy delivery issues, IEEE Power Energy Magazine, November/December, 2005, pp. 56–67.
[13] J.C. Smith,Wind of change: issues in utility wind integration, IEEE Power Energy Magazine, November/December, 2005, pp. 20–25.
[14] L.F. Wang, C. Singh,Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm, Elect.Power Syst. Res. 77 (2007) 1654–1664.
[15] R. Zavadil, N. Miller, A. Ellis, E. Muljadi, Making connections: windgeneration challenges and progress, IEEE Power Energy Magazine,November/December, 2005, pp. 26–37.
[16]SWAGATAM DAS, ARIJIT BISWAL, SAMBARTA DASGUPTA: ' Bacterial foraging optimization, theoretical,fundamental,analysis' dept of electrical jadavpur university,2006
[17] K. M. Bakwad1, S.S. Pattnaik, B. S. Sohi, S. Devi1, B.K. Panigrahi, Sanjoy Das, M. R. Lohokare- Hybrid Bacterial Foraging with Parameter free PSO.
[18] A. Farhat, Student Member, IEEE, and M. E. El-Hawary, Fellow, IEEE- Modified Bacterial Foraging Algorithm for Optimum Economic Dispatch.
[19] Gál , L.T. Kóczy and R. Lovassy- Three Step Bacterial Memetic Algorithm.
[20] Hai Shen, Yunlong Zhu, Xiaoming Zhou, Haifeng Guo, Chunguang Chang- Bacterial Foraging Optimization Algorithm with Particle Swarm Optimization Strategy for Global Numerical Optimization.