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Comparative Study and Application of Intelligence Techniques for Combined Economic and Emission Dispatch

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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. Nowadays due to increased environmental awareness, generating utilities should optimize their emission in addition to the fuel cost. Recently researchers are developing different soft computing techniques to solve the combined economic and emission dispatch (CEED) problem. In this paper some intelligent techniques have compared with each other. The compared results indicate that the proposed system results is more efficient than the terms of fuel costs, emission, total losses and computational times.

Keywords: Combined Economic and Emission dispatch; Economic Dispatch; Evolutionary techniques; Multiobjective optimization**.**

I. introduction

Economic dispatch (ED) is one of the most important

problems to be solved in the operation and planning of a power system. The main goal of the economic dispatch (ED) of electric power generation is to meet the load demand at minimum operating cost by maintaining proper schedule of the committed generating unit outputs while satisfying all unit and system equality and inequality constraints [1]. The ED problem is a large-scale highly non-linear constrained optimization problem. The classical Economic Load Dispatch (ELD) problem is to operate electric power systems so as to minimize the total fuel cost. This single objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil fueled electric power plants. Indeed, the clean air act

amendments have been applied to reduce SO2 and NOx emissions from such power plants. Hence, emissions can be reduced by dispatch of power generation to minimize emissions instead of or as a supplement to the usual cost objective of economic dispatch. The EED problem is a multi-objective problem with conflicting objectives because pollution is conflicting with minimum cost of generation. A summary of environmental and economic dispatch algorithms dating back to 1970 by using conventional optimization methods was reviewed in [2]. The problem of EED in [3] is reduced to a single objective problem by treating the emission as a constraint with a permissible limit. However, this formulation has a severe difficulty in getting the trade-off relations between cost and emission. Various strategies to reduce the atmospheric emissions have been proposed and discussed. Accordingly, in [4-6] use multi-objective Genetic Algorithm (GA), hierarchical system approach [1], fuzzified multi-objective particle swarm optimization algorithm [7], fuzzy linear programming [8-9], fast Newton-Raphson algorithm [10], linear programming

ELD problem can be solved either by considering Incremental cost or Real power as the decision variable. In this paper the authors developed a hybrid differential evolutionary algorithm with Incremental cost as the decision variable to solve CEED problem with valve point effects. CEED simultaneously optimize the two conflicting objectives economic dispatch and emission dispatch. The different objectives combine into single objective function with the help of price penalty factor. The compared results of the techniques indicate the one technique is more efficient than the others[11].

II. Problem Statement

It is clear that, the EED problem targets to find the
optimal combination of load dispatch of generating units
and minimizes both fuel cost and emission while satisfying the total power demand. Therefore, EED

consists of two objective functions, which are economic
and emission dispatches. Hence, the ELD, considering system loss can reasonably improve real and reactive power dispatch simultaneously [12]. Therefore, the ELD
problem should be considered as a multi-objective optimization problem which is based on economic, environment and system loss. The EED problem can be
Formulated as follows:

A. Minimization of Fuel Cost

The generator cost curves are represented quadratic functions and the total fuel cost $F\ (PG)$ in (\$/h) can be expressed as

$$F(P_G)=\sum_{i=1}^{N} a+b_iP_{Gi}+c_iP^2_{Gi} \qquad (1)$$

where N is the number of generators; ai , bi , ci are the cost coefficients of the i^{th} generator and P_{Gi} is the real power output of the i^{th} generator; PG is the vector of real power outputs of generators and defined as

$$P_G = [\ P_{G1}\ ,P_{G2},\ldots,\ P_{GN}\ ] \qquad (2)$$

B.Minimization of Emission

The classical ED problem can be found by the amount of active power to be generated by units at minimum fuel cost, but it is not considered as the amount of emissions released from burning fossil fuels. The total amount of emission such as SO2 or NOx depends on the amount of power generated by unit [13-14]. The minimum emission dispatch optimizes the above classical economic dispatch including NOx emission objective, which can be modeled using second order polynomial functions:

$$E\ (P_G) = \sum_{i=1}^{N} 10^{-2}(\alpha i+\beta_i{}^{p}{}_{Gi} +\gamma_i{}^{p2}{}_{Gi}) + \xi_i \exp\ (\lambda_iP_{Gi})$$

(3)

Where α_i ,β_i,γ_i,ξ_i and γ_i are the coefficient of the i^{th} generator emission characteristics.

C. Constraints

1) *Generation Capacity Constraint*

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

$$P_{Gi}{}^{min} \leq\ \ P_{Gi} \leq P_{Gi}{}^{max} \qquad i=1,2,\ldots,N$$

(4)

2) *Power Balance Constraint*

The total electric power generation must cover the total electric power demand PD and the real power loss in transmission lines P_{loss}, hence

$$\sum_{i=1}^{N} PGi - PD - Ploss=0$$

(5)

The transmission losses can be evaluated by means of B-matrix method that is taken into account so as to achieve the accurate economic dispatch.

$$P_{loss}=\sum_{i=1}^{N}.\sum_{j=1}^{N} P_I B_i \sum_{ij} P_j+\sum_{i=1}^{N} B_{io}P_i+B_{OO} \qquad (6)$$

Where,
Pj-the output generation of unit j(MW).
Bij - the ijth element of the loss coefficient square matrix.
BiO - the ith element of the loss coefficient.
BOO -the loss coefficient constant.

D .Problem Formulation

According to the above equations, the mathematical
formulation of multi-objective optimization problem is
presented as:

$$\min_{PG}[F(P_G), E(P_G), P_L(P_G)]$$
$$\text{subject to: } g(P_G)=0 \text{ and } h(P_G) \leq 0$$

(7)

Where g is the equality constraint representing the power balance, while $/i$ is the inequality constraint representing the generation capacity .The price penalty factor h blends the emission with fuel cost and cD is the total operating cost in \$/hr.

The price penalty factor $/ii$ [1] is the ratio between the maximum fuel cost and maximum emission of corresponding generator.

$$h_i = \frac{F(P_{G_i}^{max})}{E(P_{G_i}^{max})} \quad \$/lb \quad i=1,2,\ldots,N \qquad (8)$$

III. Particle Swarm Optimization

This optimization technique was developed by Kennedy and Eberhart[15,16].This artificial intelligence method was motivated by social behavior of animals such as scooling of fish,swarm of birds,etc for searching of food. This is a stochastic global search method The main idea is,the animal which moves in a group has certain criteria to share the information regarding the food, location etc In this the initial search is starts with a some random particles. Each particle indicates the possibility of a solution and it gets iterated for some iteration and converges to a global solution. In each iteration the particle has information regarding the current position, previous position and velocity. The formulas used to update position and velocity of each particle given as follows [17].

Pj-the output generation of unit j(MW).

Bij - the ijth element of the loss coefficient square matrix.

BiO - the ith element of the loss coefficient.

BOO -the loss coefficient constant.

$V'_{K+1} = \eta_K + v'_K + \alpha\eta_1(Fbest' - X'_K) + \beta\eta_2(Gbest - X'_K)$ (10)

Where,

X'_k = position of the ith particle in the Kth iteration.

V'_K = Velocity of the ith particle in the Kth iteration.

η_K=Weighting factor for the Kth iteration

α and β are constants and also acts as accelerating factors whose values are taken as 2. r_1 and r_2 are positive numbers whosw range is[0 to 1].

$Fbest'$=Local best value of ith particle.
Gbest=Global best value in the entire population.
η_K is defined as in equation (11).
η_K=

iteration$_{Max}$= Maximum iteration

The below flowchart shown in fig.1 describes the sequence of steps that takes place in a particle swarm optimization

The new position and velocity can be updated by using equations (9) and (10) respectively.

$X'_{K+1} = X'_k + V'_{K+1}$ (9)

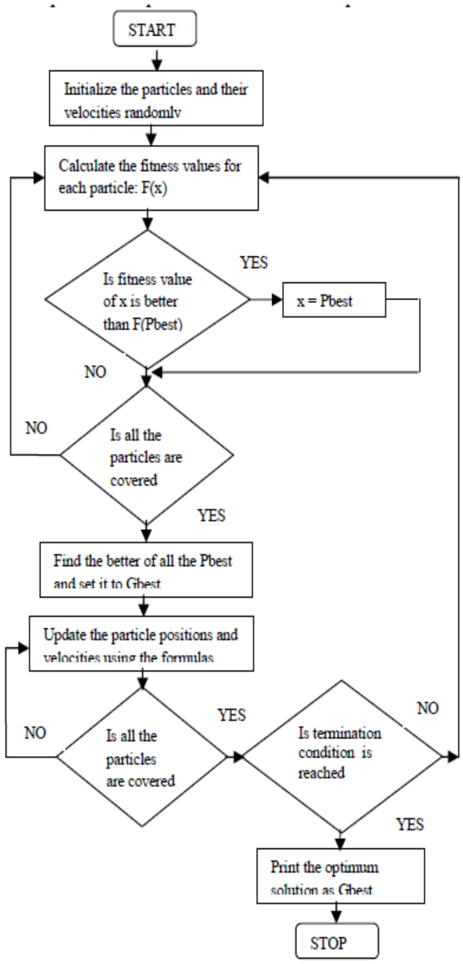

Fig.1 Flowchart for PSO

Implementing the PSO to CEED

Step 1: Read all the data of the system. Initialize the particles (powers) and their velocities randomly.

Step 2: Check for the validity of the particles whether they are satisfying the system constraints or not.

Step 3: Now calculate the Fitness function for every valid particle in iteration and get the best particle as pbest.

Step 4: Set Gbest as best of all the Pbest particles.

Step 5: Update the particle positions and their velocities.

Step 6: Go to step 2 and repeat the successive steps until the termination condition is reached.

IV. Ant Colony Optimization

A. Behavior of real ants

Ant colony optimization (ACO) studies are inspired from the behavior of real ant colonize that are used to solve function or combinatorial optimization problems. Ant colony search algorithms, to some extent, mimic the behavior of real ants. In fact, real ants are capable of finding the shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the environment. The studies by entomologists reveal that such capabilities are essentially due to what is called "pheromone trails", which ants use to communicate information among individuals regarding path and to decide where to go [18]. Ants deposit a certain amount of pheromone to follow a direction rich in pheromone rather than a poorer one.

For example, consider the behavior of ants finding a shortest path, once the old one is no longer feasible due to a new obstacle. The process can be clearly illustrated in fig 2. Where, ants are moving on a straight line that connects a food source to their nest. Ants deposit pheromone while walking and probabilistically prefer to follow a direction rich in pheromone.

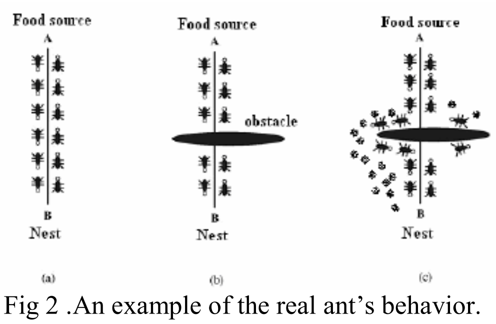

Fig 2 .An example of the real ant's behavior.

Fig.2 Real nets follow a path between nest and food source.

(b) An obstacle appears appears on the path: ants choose whether to turn left or right with equal probability.
Pheromone is deposited more quickly on the shorter path. All ants have chosen the shorter path.

This behavior can be explained how ants can find the shortest path that reconnects a line that is broken by an obstacle in fig 2(b). On introducing, those ants are just in front of the obstacle and they cannot continue to go. Therefore they have to choose between turnings right to left. Half the ants decide to turn right and the other half decide to turn left. A similar situation arises on the other side of the obstacle. Ants choosing the shorter path will more rapidly reconstitute the interrupted pheromone trail compared with those choosing the longer path. Thus, the shorter path will receive a greater amount number of ants will choose the shorter path. Due to this positive feedback, all the ants will rapidly choose the shorter path Fig.2.All ants moves at approximately the same speed and deposit a pheromone trail at approximately the same rate. The time to go round the longer side of an obstacle is greater than the shorter. This makes the pheromone trail accumulate more quickly on the shorter side. Ants prefer higher pheromone trail levels causing this accumulation to build up still faster on the shorter path.

B. *Ant colony search Algorithm*

The algorithms described as follows [18].

1. Initialize the ACO-based optimization Problem. Construct searching space including the states and stages of the optimization problem and set the ant number and the parameters of the ACO algorithm.

2. Find the paths for the ant dispatch. Each ant chooses the states to complete to tour according to a probabilistic state transition rule. Ants prefer to move to states, which are connected by shorter edges with a high amount of pheromone. Once all ants have finished their tours, some fitness functions of the optimization problem can be used to evaluate the performance of the ants.

3. Update the pheromones of edges between each stage. The pheromone trail of each edge will evaporate over time, i.e., it loses intensity if no more pheromone is laid down by the other ants. For those edges that ants traveled in this iteration, their pheromone-updating rule. Global and local pheromone updating rules are generally used to update the pheromone trail.

(i) Local Updating Rule

While constructing its tour, each ant modifies the pheromone by the local updating rule, this can be written below

$$\Gamma\ (i,j) = (1-\rho)\ \Gamma(i,j) + \rho\Gamma_0 \quad (11)$$

Where,

Γ_o - the initial pheromone value
ρ - is a heuristically defined parameter.

The local updating rule is intended to shuffle the search process. Here, the desirability of paths can be dynamically changed. The nodes visited earlier by a certain ant can be also explored later by the other ants. The search space can be therefore extended.

(ii) Global Updating Rule

When tours are completed, the global updating rule is applied to edges belonging to the best ant tour. This rule is intended to provide a greater amount of pheromone to shorter tours, which can be expressed below:

$$\Gamma(i,j) = (1-\sigma)\ \Gamma(i,j) + \sigma\delta-1 \quad (12)$$

Where,
δ- is the distance of the globally best tour from the beginning of the trial.
σ- is the pheromone decay parameter.
This rule is intended to make the search more directed; therefore the capability of finding the optimal solution can be enhanced through this rule in the problem solving process.

4. Defined the convergence criteria of the problem. This process is iterated until the tour counter reaches the maximum pre-defined number of iterations or all ants make the same tours.

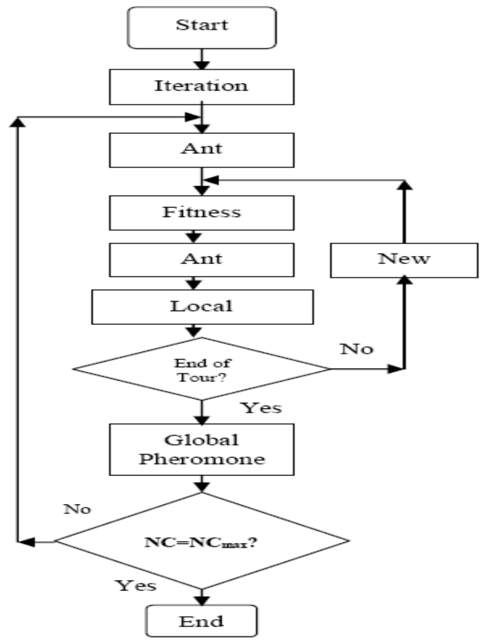

Fig.3. The flowchart of ACSA for EED program

V. Cuckoo Search Algorithm

Cuckoo Search (CS) is a stochastic global search algorithm formulated by Yang and Deb [15-16]. It is inspired from the breeding strategy of some cuckoo species by laying their eggs in the nest of host birds.

Cuckoo bird searches for a nest where they could lay their eggs. As cuckoo eggs would hatch earlier as those of host birds, so they choose a nest where host bird has just laid its eggs. When a cuckoo egg is hatched, it instantly expels the host bird's eggs so as to receive all the food brought in. If host bird discovers cuckoo egg then either it throw away those

alien eggs or abandon its nest or build a new nest somewhere. Some breeds of cuckoos have adapted to lay their eggs which mimic the eggs of host birds. This characteristic decreases the probability of their eggs being abandoned and thus increases their reproductively. In simulation, each nest represents apotential solution. CS idealized this breeding behavior of
cuckoo species for various optimization problems in threesteps:
1. Each cuckoo lays only one egg in the randomly chosen
nest.
2. The best nests with better proficiency will carry to the
next generation.
3. Here the availability of host nests is fixed and probability paϵ [0, 1] represents the possibility of alien egg to be discovered by host bird.
The new nest i.e. new solutions x_i^{t+1} are generated by the
host by the Lévy flight method [21].

$$x_i^{t+1} = x_i^t + \alpha \oplus Levy(\beta) \quad (13)$$

where $\alpha > 0$, represents the step size of the concern problem. The product $\oplus$ means entry wise multiplications.

$$\alpha = \alpha_o\,(x_j^t - x_i^t) \quad (14)$$

where $\alpha 0$ is constant, while the term in the bracket represent the difference of two random solutions. This mimics that fact that similar eggs are less likely to be discovered and thus new solutions are generated by the proportionality of their difference.

Normally, Lévy flights represent a random way of food
searching used by birds and animals. It is suggested that the step size should be L/100, where L is the size of space to be searched. Selection of larger step size would lead new solutions to go out

of search space. The generation of random walks by Lévy flights can be achieved either by randomization through Lévy distribution or by normal distribution. By Lévy distribution, the step length can be derived as:

$$\text{Lévy} \sim u = t1\text{-}\beta \quad (0<\beta<2) \tag{15}$$

which has an infinite variance and infinite mean. Here, β=1.5.

A fraction of worse nests can be thrown away with probability (pa) so that new nests can be built by random walk or mixing. The mixing of eggs can be performed by random permutation according to the similarity/difference of the host eggs. A scheme for the calculation of step size is discussed in detail [19] can be summarized as:

$$s = \alpha_0 (x_j^t - x_i^t) \oplus Levy(\beta) \sim 0.01 * \frac{u}{|v|^{1/\beta}} (x_j^t - x_i^t)$$

(16) where, u and v are drawn from normal distribution. That is:
$u \sim N(0, \sigma u^2)$ & $v \sim N(0, \sigma v^2)$

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2\beta 2^{\beta-1/2}]} \right\}^{1/\beta}, \ \sigma_v = 1$$

(17)
Γ represents the standard gamma function.

$$\Gamma(z) = \int_0^{\infty} t^{z-1} e^{-t} dt$$

where, z=k is a integer, we have Γ(k)= (k-1)!.

II. V. IMPLEMENTATION

The computational process of CS can be described in the following steps:

Step 1: Initialize the number of population, *n* of host nests through objective function (1) as *f(x), x=(x1, x2…….xd)* within generation range . Specify the capacity of each generator, cost characteristics, emission coefficients matrix. Set the value of probability, pa and maximum number of iterations
.
Step 2: While the iteration value is less than the maximum number of iterations, the function will generate a cuckoo randomly by Lévy flight using (23-25). Since each value of population set represents the power generation output which acts as decision variables for CEED.
Step 3: Estimate the fitness *Fi* of the generated solution. In CEED problem, fitness value signifies the overall fuel cost and emission for *ith* thermal units which is evaluated with the help of (i).
Step 4: Choose a nest among *n* (say *j*) randomly and
calculate its fitness (*Fj*) as in Step 3.
Step 5: Perform selection procedure between *Fi* and *Fj* based on their fitness values. If the fitness *Fi* is more than the fitness *Fj* then replace *j* by new solutions.
Step 6: A fraction of worse nests (not so good solutions) are discarded and new ones are built by Lévy flights according to (13-14) and (16-17).
Step 7: As the new solutions are accepted, rank the solutions and find the current best solutions.

$$TC = \min \sum_{i=1}^{N_g} f_i(F(P_i), E(P_i))$$

(i)

VI. Comparision Table

S.NO	Performance	PSO	ACO	CS	HDEA
1.	Fuel cost ($/hr)	_	Cost Minimizing	_	_
2.	Emission Kg/hr)	_	Reduce Emission	_	_
3.	Simulation Time(Sec)	_	_	More Speed	_
5.	Power Losses (p.u)	_	_	_	Reduction in Power loss

VII. Conclusion

Combined Economic and Emission Dispatch problem has become an active area of research in the field of power system. It has been observed that the CEED problem can be solved by optimization algorithm like PSO, ACO, CS, IWD-CO etc. The results of the given optimization technique given HDEA is better than PSO and DEA it considerable reduction in power loss. ACO is better than PSO which reduces the total emission and there by total cost. Cuckoo method is more efficient than the others in term of speed and quality of solutions. IWD-CO is having better convergence in terms of best average time to the others.

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