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Modeling of Power System for Minimization of Cost by Fuzzy Unit Commitment

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Abstract: ***In planning of power system the unit commitment plays a crucial role. For sake of optimal dispatch of generating unit commitment is extensively applied. By the unit commitment process we can determine the turn on and turn off times for generators. This paper put forward the implementation of fuzzy modeling to determine the uncertainty constraints like load forecasting and fuel cost. Intelligence technique Differential Evolution Immunized Ant Colony Optimization for unit commitment problem. The verification process was performed on IEEE 30-bus test system. A MATLAB code was implemented for fuzzy unit commitment and Differential Evolution Immunized Ant Colony Optimization technique and cost solution is presented.***

Keyword: fuzzy unit commitment, particle swarm optimization, Differential Evolution Immunized Ant Colony optimization

1. Introduction

Now-a-days electric power occupies a crucial role in human life. Due to adverse effect of population increase demand of power also increase. It is essential to maintain and operate the system to meet the estimated load. In this condition various problems involve such as unit commitment, economic load dispatch and load forecasting. Unit commitment is selection of units that will achieve the load demand at low cost. Unit commitment problem is a mixed integer optimization problem. The main goal of it is to estimate the periodic operation of generators at the same time to satisfy system and unit constraint. Load forecasting and fuel cost are uncertainties associated with the unit commitment. Neglecting these uncertainties may cause inappropriate solution or else may be applicable to some conditions. So there is need to incorporate these constraints into unit commitment problem.

For solving this technique we have deterministic, meta-heuristic and hybrid approaches are available. Deterministic approach includes priority list method dynamic programming, LAGRANGIAN relaxation mixed-integer programming and branch and bound method. Though these method provides solution in simplest and fastest way but faces a fast convergence and poor final solution.

In capability of conventional methods to achieve optimal solution proposes the development of the artificial intelligence and meta-heuristic techniques into unit commitment solution. Some of them are genetic algorithm, evolutionary programming, harmonic search, differential evolution and particle swarm optimization. These are capable to memorize the best solution of search space. Any way they only provide near optimal solution. Meta-heuristic techniques like differential evolution and particle swarm optimization are introduced into unit commitment. Despite their fast convergence they provide near optimal solution.

So in this paper proposes the implementation of fuzzy modeling to involve the uncertainty constraints into unit commitment problem. Fuzzy was proposed by Zadeh in 1965, it was a probabilistic logic that deals with approximation process. Fuzzy modeling deals with the imprecision resulting from the linguistic terms, the randomness, the ambiguity expression, vagueness and inaccuracy. In this research fuzzy modeling is used to determine the fuel cost and load demand. And also in addition to that, implementation of DEIANT technique to solve fuzzy unit commitment is done. This is a hybrid of differential evolution and ant colony optimization technique.

2. Fuzzy Unit Commitment

To determine the optimal on/off schedule of units that yields the minimum total cost over the horizon period while satisfying the problem constraints. Fuzzy theory make use of the membership function. Membership function is denoted by *Mx* and the function will correspond to the characteristic function *Xi* varies from zero to one. It is desired to get the membership function as close to 1.0 as possible. The mapping characteristics are based on triangular fuzzy set. Membership function can be expressed as,

$$M_D \begin{cases} 0 \ if \ P_D < (D - \Delta D_1) \\ \frac{P_D - (D - \Delta D_1)}{\Delta D_1} \ if \ (D - \Delta D_1) \le P_D < D \\ 1 \ if \ P_D = D \\ \frac{(D + \Delta D_2) - P_D}{\Delta D_2} \ if \ D < P_D \le (D + \Delta D_2) \\ 0 \ if \ P_D > (D + \Delta D_2) \end{cases}$$

Where:
M_D Demand membership
P_D Calculated power demand
D Actual demand
$\Delta D_1, \Delta D_2$ Demand changes.

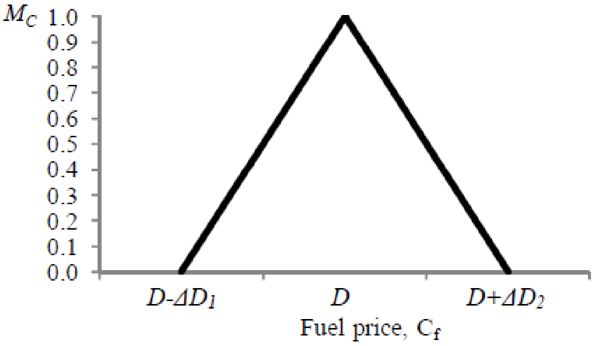

Figure 1: Triangular fuzzy set for load demand

The fuel cost is also represented by triangular membership function

$$M_c \begin{cases} 0 \; if \; C_f < (C - \Delta C_1) \\ \frac{C_f-(C-\Delta C_1)}{\Delta C_1} \; if \; (C - \Delta C_1) \le C_f < C \\ 1 \; if \; C_f = C \\ \frac{(C+\Delta C_2)-C_f}{\Delta C_2} \; if \; C < C_f \le (C + \Delta C_2) \\ 0 \; if \; C_f > (C + \Delta C_2) \end{cases}$$

Where:
Mc Fuel price membership
C_f Calculated fuel price
C Actual fuel price
$\Delta C_1, \Delta C_2$ Fuel cost charges

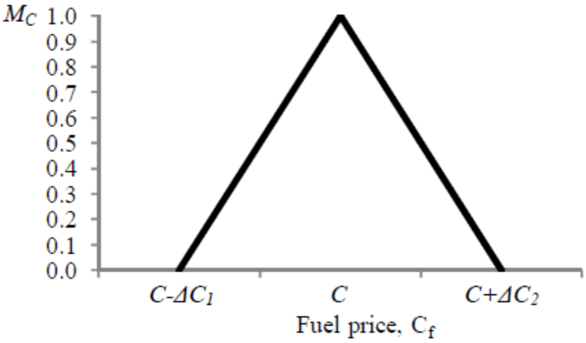

Figure 2: Triangular fuzzy set for fuel price

Unit commitment can be described as in equation:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c$$

Where C_i is operating cost of unit i. a_i , b_i and c are the cost factor of unit i.
Summation of unit commitment in the system is given by,

$$C_{total} = \sum_{i}^{ng} C_i(P_i)$$

Inequality constraint of generation limits for each unit,

$$P_{i\ min} \le P_i \le P_{i\ max}$$

Where $P_{i\ min}$ and $P_{i\ max}$ are minimum and *maximum generation limits.*

$\sum_i^{ng} P_{gi} = P_D + P_{loss}$

P_{loss} can be calculated by following equation

$$P_{loss} = \sum_{i}^{n} \sum_{j}^{n} P_i B_{ij} P_j + \sum_{i}^{n} B_{0i} P_i + B_{00}$$

3. Differential Evolution Immunized Ant Colony Algorithm

The capability to achieve fast convergence has been identified as the attractive feature of DE. This feature will be used to compensate the stagnation of ACO algorithm. The modification of ACO algorithm will be focusing on the pheromone updating rule which is subjected to cloning, mutation, crossover, and selection process. Overall structure and processes of Differential Evolution Immunized Ant Colony Optimization (DEIANT) algorithm has been explained.

a. Introduction

As deiant is a hybrid model of aco so it contains several similar parameters of aco. Such as the initial number of ant, nodes, pheromone decay parameter, α, and the initial pheromone level, τ_0 these are heuristically initialized. Simply to avoid large computation time the maximum distance travelled by ant is subjected to constraint. Dmax is achieved by calculating the longest tour done by the ant.Each ant will tour and select the next unvisited node until all nodes have been visited.

b. Apply State Transition Rule

This is to judge which node has to be visited by the ant in tour. Each node can be visited once. Next unvisited node is chosen according to state transition rule. If so ant was positioned at node r it will go to next node s.

$$P_k(r,s) = \left\{ \frac{[\tau(r,s).\eta(r,s)^{\beta}]}{\sum_{\mu \varepsilon J_{k_r}} [\tau(r,s)].[\eta(r,s)^{\beta}]} \right.$$

Where r is the current node, s is next node and u is unvisited node.

c. Apply Local Updating Rule

Whileforming the solution the level of pheromone deposition has to be varied. Amount of pheromone is either maximized or minimized to alter the attractiveness of route via the evaporation rate, ρ. Each ant will update pheromone level by evaporation rate and it is needed to avoid algorithm converge pre-maturely. The parameter act as multiplier and is set in between 0&1.

d. Pheromone Cloning

The process of cloning is adapted from artificial immune system and implemented in to deiant technique. Pheromone level will be duplicated to maximize pheromone population.

e. Pheromone Mutation

It is need to enhance the pheromone layer over visited node of ant tour during exploration. This process is called mutation. Mutation coefficient can be either user defined or calculated by distribution function. In this research we use Gaussian distribution function.

$$X_{i+m} = X_{i,j} + N\left(0, \beta\left(X_{j\ max} - X_{j\ min}\right).\frac{f_i}{f_{max}}\right)$$

Where:
X_{i+m} : Pheromone mutation function
$X_{j\ min}$: Smallest node number
$X_{j\ max}$: Largest node number
f_i : Travelled distance
f_{max} : Maximum distance

f. Crossover

Crossover operation is implemented to enhance the diversification vector of the pheromone trail; crossover operation will merge pheromone parents, ρ0i to produce pheromone offspring ρ_{ci}. In this algorithm the original and mutated pheromone level will be reappeared in same matrix. This matrix is sorted in descending order.

g. Selection

Pheromone trail ρ_t is the product of the crossover process. When sufficient selected number of individuals is obtained roulette wheel selection process will terminate procedure. Unselected matrix will be eliminated. The algorithm now selects the required trail according to this rule. The trail with higher pheromone level is accepted and remaining will be discarded.

$$\rho_{sel} = \begin{cases} \rho_{sel}\ , if\ pheromone\ \ level\ , \rho < \rho_{sel} \\ \rho\ , other\ wise \end{cases}$$

ρ_{sel} is the selected pheromone and ρ is original pheromone.

h. Control Variable Calculation

The control variable x will be used to find the objective function. The control variable can be calculated by equation,

$$x = \frac{d}{d_{max}} . x_{max}$$

d=distance of ant tour
d_{max} =maximum distance
x_{max} =maximum value of x

i. Global Updating Rule

At a random, the best ant of the colony will be selected after all ants complete their exploration. The data available from this ant is stored and treated as best tour. The following equation is applied to update the pheromone level globally.

j. End Condition

Probably the algorithm hits its end when maximum number of iteration has been achieved and all ants have completed their tour. Better path of the exploration is made as reference and only single ant gives the optimal path.

4. Result and Discussion

Differential evolution immunized ant colony optimization algorithm and fuzzy unit commitment problem were implemented on MATLAB. In this research the algorithm was implemented by using IEEE-30 bus system with 6 generating units. Table 1 tabulates the data for IEEE-30 system.

Table1: Generator Limits and Cost Co-Efficient of IEEE-30 Bus System

Gen No.	P_i^{max} (MW	P_i^{min} (MW)	a_i ($/MW^2-hr)	b_i ($/MW-hr)	c_i ($/hr)
1	200	50	0.00375	2.00	0
2	80	20	0.00175	1.75	0
3	50	15	0.0625	1.00	0
4	35	10	0.00834	3.25	0
5	30	10	0.0025	3.00	0
6	40	12	0.0025	3.00	0

a. Fuzzy Modeling

Unit commitment problem was solved by using conventional method (without fuzzy modeling) and fuzzy modeling and the comparison were tabulated in table II

Table 2: Comparison of Unit Commitment Solution Without And With Fuzzy Model

Units (MW)	*Without fuzzy*	*With fuzzy*
1	447.548	446.79
2	173.087	172.518
3	263.363	261.28
4	138.716	140.122
5	166.099	165.361
6	86.939	87.297
Total demand(MW)	1263	1263
Total dispatch(MW)	1275.752	1273.518
P_{loss}(MW)	12.752	10.518
Total cost(&/hr)	15447	15419.837

By referring the above table it is clear that there were several differences between generation outputs of two methods. The total dispatch calculated by fuzzy method (1273.518 MW) is smaller than the one calculated by conventional method (1275.752 MW). We can observe that fuzzy model dispatches output closer to value than the output produced by conventional methods. Loss produced by fuzzy method (10.518) is lesser than the one without fuzzy (12.752). The cost factor is also cheaper than conventional method. The cost of production in fuzzy method (15419.837 $/hr) is less than conventional method (15447 $/hr).

b. Fuzzy Unit Commitment Optimization

In this research, fuzzy unit commitment was optimized using DEIANT technique and the results are tabulated in table III below.

Table 3: Comparison fuzzy unit commitment optimization technique

Units (MW)	PSO	DEIANT
1	446.819	446.503
2	172.311	171.229
3	261.2	259.340
4	140.532	138.781
5	165.279	163.862
6	86.433	87.158
Total demand(MW)	1263	1263
Total dispatch(MW)	1272.588	1271.532
P_{loss} (MW)	9.588	8.53
Total cost ($/hr)	15413.64	15407.857

By referring the table the total dispatch is less than the fuzzy method (1273.518 MW) with comparison of DEIANT (1271.532 MW). Despite of attractiveness of the fuzzy model (10.518 MW) the PSO (9.588 MW) and DEIANT (8.53 MW) produce fewer losses. Cost is comparatively cut down when compared to fuzzy method (15419.837 $/hr) with PSO (15413.64 $/hr) and DEIANT (15407.857 $/hr). DEIANT produce best solution when compared to both fuzzy modeling and PSO.

5. Conclusion

This research gives importance to the implementation of fuzzy set modeling for finding out the uncertainty constraints to solve unit commitment problem. Negligence on the uncertainty constraint in deregulated power system comprises unexpected issues. Several techniques including PSO and DEIANT are used to optimize fuzzy unit commitment. Though fuzzy model produce better solutions the DEIANT optimization technique produces best solution for unit commitment among PSO and DEIANT.

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