UNIT COMMITMENT BY LAGRANGIAN RELAXATION INCORPORATING DIFFERENTIAL EVOLUTION

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Abstract: ***This paper proposes Lagrangian relaxation method along with differential evolution algorithm to solve the unit commitment problem. Optimal setting of Lagrangian multipliers is obtained by incorporating Differential Evolution procedure. Spinning reserve, minimum up, and down time constraints, start up cost, and generation limit constraints are taken into consideration of Problem formulation. The proposed algorithm is tested on a 10-unit system and is compared with other methods reported in the literature.***

Keywords: Differential Evolution, Unit Commitment, Lagrangian relaxation

Nomenclature

F_i^t Generator fuel cost in quadratic form.

$F_i^t = a_i + b_i P_i^t + c_i (P_i^t)^2$ \$/h.

ISO Independent system operator

k Iteration counter

N Total number of generator units.

$P_{i,\min}$ Minimum real power generation of unit i (in megawatts).

$P_{i,\max}$ Maximum real power generation of unit i (in megawatts).

P_i^t Real power generation of unit i at hour t (in megawatts)

P_i^{opt} Optimal generation output of unit i at hour t (in megawatts).

P_D^t Load demand at hour t (in megawatts).

R^t Spinning reserve at hour t (in megawatts).

ST_i^t Startup cost of unit i at hour t.

T Total number of hours.

$T_{i,cold}$ Cold start hours of unit i (in hours).

$T_{i,down}$ Minimum down time of unit i (in hours).

$T_{i,off}$ Continuously off time of unit i (in hours).

$T_{i,on}$ Continuously on time of unit i (in hours).

$T_{i,up}$ Minimum up time of unit i (in hours).

$U_{i,t}$ Status of unit i at hour t (on = 1, off = 0).

$\lambda^{t(0)}, \mu^{k(0)}$ Initial Lagrangian multiplier at hour t (in units/mwh, units/mw).

$\lambda^{t(k)}, \mu^{t(k)}$ Lagrangian multiplier at hour t at iteration k (in units/mwh, units/mw).

N_p Vector size

x_j^{max} Upper bound

x_j^{min} Lower bound

F Mutation factor

C_r Crossover probability

U_i^G Trial vector of current position

x_{ij}^G Target vector of current position

Abbreviations:

CSC_i Cold startup cost of unit i.

HSC_i Hot startup cost of unit i.

1. Introduction

In most of the interconnected power systems, the power necessity is principally met by thermal power generation. There are several operating conditions based on constraints which have to satisfy the variable demand. In recent years, higher penetration of variable generation resources (such as wind power, solar power, and distributed generators) and more price-responsive demand participation have created new challenges to the unit commitment process, especially in the independent system operator (ISO) managed electricity markets. It becomes predominant for the ISOs to have an effective methodology that produces sturdy unit commitment decisions and ensures the system reliability in

the presence of increasing real-time uncertainty [1].It is preferable to use a favourable outcome operating strategy based on economic norm. In order to deliver reliable electric power to customers in a secured and economic manner, thermal unit commitment (UC) is considered to be one of optimum available options. Since the major component of generator operating cost is fuel, economy of operation is important in determining the allocation of generation of various load levels meeting the necessary operating constraints, this problem is treated as unit commitment problem. So the general intention of the UC problem is to minimize system total operating cost while satisfying all of the constraints so that a given security level can be met [11].

A survey of literature on the UC methods divulge that various numerical optimization techniques have been employed to approach the UC problem[7].UC problem is a kind of complex, dynamic and restricted nonlinear programming which contains not only continuous variables but also integral variables[6].Many solution methodologies have been put forward in the literature for the UC problem. Lagrangian Relaxation technique is one of the prominent techniques. Lagrangian relaxation proceeds in three stages. In the first stage, the dual of the unit commitment is maximized with standard gradient techniques. The second part finds a dual solution, and in third step finds economic dispatch. This procedure gives good performance and has low execution time [14]. However, the method described does not address how to process the ramp rate constraints within the optimization problem. Later, it is extended to incorporate unit minimum capacity constraints and unit ramp rate constraints [13]. This improvised the Lagrangian algorithm but the rate of convergence is not increased. In order to improve the rate of convergence, LR algorithm is combined with Heuristic based methods which made the application of LR algorithm to modern day unit commitment challenges to achieve a precise and faster rate of convergence. The traditional methods includes priority list method (PL)], dynamic programming (DP), mixed- integer programming (MIP), branch and bound method (BB). These methods are simple and fast but they suffer from the convergence problem and poor solution. The other meta-heuristics methods adopted are genetic algorithm (GA) [2], simulated annealing (SA), evolutionary programming (EP), particle swarm optimization (PSO) [4] and ant colony optimization (ACO). These methods can execute complex problems with high quality resolution. The meta-heuristics approach provides a logical solution within a reasonable computation time. However, it has disadvantages that it cannot assure the optimality of the solution and that it is hard to evaluate the quality of the obtained solution [5]. Therefore, we must find a feasible solution by some heuristics. In this paper, an efficient algorithm differential evaluation is used along with LR to solve the UC problem.

2. Problem formulation

The objective of unit commitment problem is to minimize the production cost over the scheduled time horizon (24hours) under the generator operational and spinning reserve constraints.

The objective function to be minimized is

$$F(P_i^t, U_{i,t}) = \sum_{t=1}^{T}\sum_{i=1}^{N}[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})]U_{i,t} \quad (1)$$

Subject to the following constraints

Power balance constraint

$$\sum_{i=1}^{N} P_i^t U_{i,t} = P_D^t \quad (2)$$

Spinning reserve constraint

$$\sum_{i=1}^{N} P_{i,\max} U_{i,t} \geq P_D^t + R^t \quad (3)$$

Generator limit constraints

$$P_{i,\min} U_{i,t} \leq P_i^t \leq P_{i,\max} U_{i,t}, \; i = 1,....,N \quad (4)$$

Minimum up and down time constraints

$$U_{i,t} = \begin{cases} 1, & if \; T_{i,on} < T_{i,up}, \\ 0, & if \; T_{i,off} < T_{i,down}, \\ 0 \; or \; 1, & otherwise \end{cases} \quad (5)$$

Startup cost

$$ST_{i,t} = \begin{cases} HSC_i & if \; T_{i,down} \leq T_{i,off} \leq T_{i,cold} + T_{i,down}, \\ CSC_i & if \; T_{i,off} > T_{i,cold} + T_{i,down} \end{cases} \quad (6)$$

3. Lagrangian relaxation

The LR procedure solves the UC problem by relaxing or temporarily ignoring the coupling constraints and solving the problem as if they did not exist. The is done through the dual optimization

$$L(P, U, \lambda, \mu) = F(P_i^t, U_{i,t}) + \sum_{i=1}^{T} \lambda^t (P_D^t - \sum_{i=1}^{N} P_i^t U_{i,t}) + \sum_{t=1}^{T} \mu^t (P_D^t + R^t - \sum_{i=1}^{N} P_{i,max} U_{i,t}) \quad (7)$$

with respect to nonnegative λ^t and μ^t whereas minimizing it with respect to other control variables in the problem, that is

$$q^*(\lambda,\mu) = Max_{\lambda^t,\mu^t}\, q(\lambda,\mu) \quad 8$$

Where

$$q(\lambda,\mu) = Min_{P_i^t,\, U_{i,t}} L(P,U,\lambda,\mu) \quad 9$$

Equations (2) and (3) are the coupling constraints across the units. In particular, what is done to one unit affects the other units. The Lagrangian function is rewritten as

$$L = \sum_{t=1}^{N}\sum_{i=1}^{T}\{[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})]U_{i,t} - \lambda^t P_i^t U_{i,t} - \mu^t P_{i,max} U_{i,t}\} + \sum_{t=1}^{T}(\lambda^t P_D^t + \mu^t(P_D^t + R^t)) \quad 10$$

The term $\sum_{i=1}^{T}\{[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})]U_{i,t} - \lambda^t P_i^t U_{i,t} - \mu^t P_{i,max} U_{i,t}\}$ can be minimized separately for each generating unit, when the coupling constraints are temporarily ignored. Then, the minimum of the Lagrangian function is solved for each generating unit over the time horizon, that is

$$\mathrm{Min}_{P_i^t,\, U_{i,t}} L(P,U,\lambda,\mu) = \sum_{i=1}^{N} \min \sum_{t=1}^{T}\{[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})]U_{i,t} - \lambda^t P_i^t U_{i,t} - \mu^t P_{i,max} U_{i,t}\} \quad 11$$

Subject to $U_{i,t}P_{i,min} \le P_i^t \le U_{i,t}P_{i,max}$

for t=1,...,T and the constraints in (5)

On/Off decision criterion:

In the Lagrangian relaxation method, the dual solution is obtained by using dynamic programming for each unit separately. This can be visualized in fig.1 showing the only two possible states for unit i (i.e, $U_{i,t} = 0\ or\ 1$) at the $U_{i,t}$=0 state, the value of the function to the minimized is trivial (i.e., it equals zero), at the state where $U_{i,t}$=1, the function to be minimized is (the startup cost and the term $\mu^t P_{i,max}$are dropped here since the minimization is with respect toP_i^t)$min[F_i(P_i^t) - \lambda^t P_i^t]$

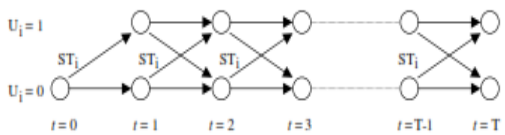

Fig.1. Two-state dynamic programming

To find the dual power, the term $\min[F_i(P_i^t) - \lambda^t P_i^t]$ will be minimized by the optimality condition

$$\frac{d}{dP_i^t}[F_i(P_i^t) - \lambda^t P_i^t] = 0 \quad 12$$

The solution to this equation is

$$\frac{dF_i(P_i^{t,dual})}{dP_i^t} = \lambda^t \quad 13$$

The dual power is obtained

$$P_i^{t,dual} = \frac{\lambda^t - b_i}{2c_i} \quad 14$$

There are three cases to check $P_i^{t,opt}$ against its limits

1) If $P_i^{t,dual} < P_{imin}$, then $P_i^t = P_{imin}$
2) If $P_{imin} \le P_i^{t,dual} \le P_{imax}$,then $P_i^t = P_i^{t,dual}$
3) If $P_i^{t,dual} > P_{imax}$, then $P_i^t = P_{imax}$

Dynamic programming is used to determine the optimal schedule of each unit over the scheduled time period. More specifically, for each state in each hour, the on/off decision making is needed to select the lower cost by comparing the combination of the start-up cost and accumulated costs from two historical routes. The dual power calculated and within the limit, will be substituted in the new on/off decision criterion.

$$[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})] - \lambda^t P_i^t - \mu^t P_{i,max}^t \quad 15$$

To minimize the above term in (15) at each hour, if $[F_i(P_i^t) + ST_{i,t}(1-U_{i,t-1})] - \lambda^t P_i^t - \mu^t P_{i,max}^t \le 0$, this unit will be committed if it does not violate the minimum downtime constraint ($U_{i,t}$=1). Otherwise this unit will not be committed if it does not violate the minimum uptime constraint ($U_{i,t}$=0).

4. Overview of DE Algorithm

DE was presented as a heuristic optimization method that can be used to optimize nonlinear and non differentiable continuous space functions with real-valued parameters by Storn and Price. It is stochastic, population based algorithm. The major feature of DE is that it uses random distinct sampled pairs of object vectors to guide the mutation operation as a substitute for probability distribution functions as other EAs. The distribution of the distinct random sampled object vectors is resolved by the distribution of these objects vectors. Because the distribution of the object vectors is mainly determined by the corresponding objective function's topography, the biases where DE tries to optimize the problem match those of the function to be optimized. This entitles DE to function effectively and more as a generic global optimizer than other EAs.

According to Price [3], the main advantages of DE include fast application and modification, simple and easy to implement, effective global optimization capability, parallel processing nature, operating on floating point format with high precision, efficient algorithm without sorting or matrix multiplication, self-referential mutation operation, effective on integer, discrete, and mixed parameter optimization, ability to handle non differentiable, noisy, and/or time-dependent objective functions

Differential Evolution (DE) is an evolutionary algorithm based on the populations of possible candidate solutions with three operators: mutation, crossover and selection. In DE, candidate solutions are identified by vectors and set of vectors generate the population. The basic notation is to form new vector by means of the weighted difference between the two population vectors. These three vectors are chosen randomly. Then the fitness of the new vector is checked. If the fitness of the new vector is better than the previous two, then exchange takes place.

Initially population vector of size N_p are generated randomly in the D-dimensional search space over a generation G as follows:

$$x_{ij} = rand * \left(x_j^{max} - x_j^{min}\right) + x_j^{min} \quad 16$$

Where i = 1, 2, N_P denotes the individual's population index and j = 1, 2, D signifies the D-dimensional search space position. $rand$ is a uniformly distributed random number varies between 0 to 1. The upper bound and lower bound of the decision parameter are symbolized by x_j^{max} and x_j^{min}respectively.

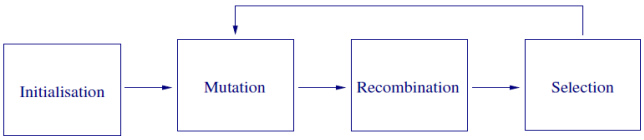

Fig. 2: Basic steps in Differential Evolution Algorithm

Mutation:

A mutant vector, for each target vector x_i^G is formed as:

$$V_i^{(G-1)} = x_k^{(G)} + F * (x_l^{(G)} - x_m^{(G)}) \quad 17$$

Where k, l, and m are randomly chosen vectors {1, 2…..N_p}. Further k, l and m should be different so that N_p > 4 is required. The mutation factor F is an experimentally chosen parameter that is used to regulate the amplification of the difference between two individuals to escape search stagnation.

Crossover:

After mutation, crossover is applied to the population. For each mutant vector, a trial vector is generated as follows:

$$U_i^G = u_{ij}^G = v_{ij}^G, if \ \ rand_j(0,1) < C_r \ or \ j = j_{rand}$$

$$= x_{ij}^G, otherwise \quad 18$$

Where C_r is a crossover probability and it is fixed parameter used to create trial vectors at all generations,j_{rand} a newly generated random value for each i.

Selection:

The selection procedure compares the trial vector U_i^G and target vector $x_{ij}^G$of current position and the vector with the better fitness are allowed to enter the next generation.

$$x_{ij}^{G+1} = U_i^G, if \ f\left(U_i^G\right) < f\left(x_{ij}^G\right)$$

$$= x_{ij}^G, otherwise \quad 19$$

5. proposed Method

In this paper LR method is used to solve the UC problem. The Lagrangian multipliers are initialized and updated by the DE algorithm. Flowchart of the proposed method is presented below.

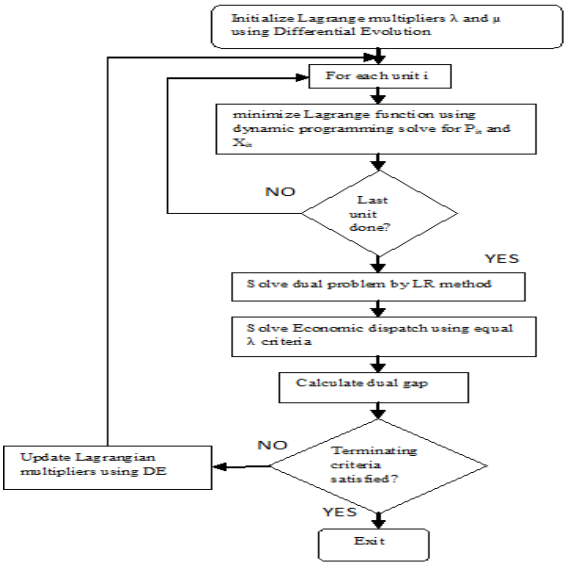

Fig. 3: Flow chart of Solving UC Problem by DE

6. Results:

The proposed algorithm for solving unit commitment problem was programmed in MATLAB of version 2010a environment with Pentium dual core, 3.2 GHz computer with 3 GB RAM. The test system consisting of ten power generating units and a time horizon of 24hours is taken from [12]. In DE the population consists of 40 individuals. In lambda iteration, the tolerance is set to 0.0001.The fitness value of each individual is calculated as the summation of the fuel cost, start up cost and the penalty value. The cost for power generation is calculated using lambda iteration based on the status of each power generating unit. For each hour depending on whether the start up is cold start or a hot start, the appropriate cost is added to the total cost. A penalty term is used if the hourly power demands plus a specific amount of reserve is not meant or if t_{up} and t_{down} constraints are violated. All parameter values are determined using the best settings formed as a result of a series of 10 runs. The mutation

constant, F and crossover constant C_r taken are 0.5 and 0.8 respectively.

The fitness function is given below:

$$f = \sum_{t=1}^{T}\{\sum_{i=1}^{N}[F_i(P_i^T) + ST_{i,t}(1 - U_{i,t-1})]U_{i,t} + kP(xi - xilim)2\} \quad 20$$

where K_p is the penalty factor for the dependent variables. The performance of DE is compared with other methods resulted in optimizing the cost of ten generating units is shown in table 1,table 2 shows the load demand and DE solution of ten unit system and table 3 is the optimal setting of Lagrangian multipliers . The best overall cost obtained using DE is approximately $564180. The fitness variation and cost variations are shown in fig. 4 and fig. 5 respectively for 100 iterations. The CPU run time for the following test system run is approximately 128 sec.

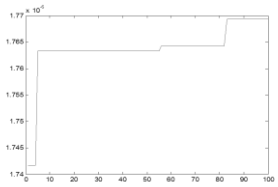

Fig.4: fitness vs. iterations

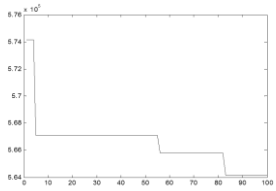

Fig. 5: cost vs. iterations

Table 1: comparison of total production costs ($)

Units	Total Production Cost($)					
	DP (12)	LR (8)	GA (12)	EP (10)	SPL (9)	DE
10	565825	565825	565825	565352	564950	564180

Table 2: load demand and DE solution of the ten unit system

No. Of hrs.	Load	Generator number 1 2 3 4 5 6 7 8 9 10	No Of hrs	Load	Generator Number 1 2 3 4 5 6 7 8 9 10
01	700	1 1 0 0 0 0 0 0 0 0	13	1400	1 1 1 1 1 1 1 1 0 0
02	750	1 1 0 0 0 0 0 0 0 0	14	1300	1 1 1 1 1 1 1 0 0 0
03	850	1 1 0 0 1 0 0 0 0 0	15	1200	1 1 1 1 1 0 0 0 0 0
04	950	1 1 0 0 1 0 0 0 0 0	16	1050	1 1 1 1 1 0 0 0 0 0
05	1000	1 1 0 1 1 0 0 0 0 0	17	1000	1 1 1 1 1 0 0 0 0 0
06	1100	1 1 1 1 1 0 0 0 0 0	18	1100	1 1 1 1 1 0 0 0 0 0
07	1150	1 1 1 1 1 0 0 0 0 0	19	1200	1 1 1 1 1 0 0 0 0 0
08	1200	1 1 1 1 1 0 0 0 0 0	20	1400	1 1 1 1 1 1 1 1 0 0
09	1300	1 1 1 1 1 1 1 0 0 0	21	1300	1 1 1 1 1 1 1 0 0 0
10	1400	1 1 1 1 1 1 1 1 0 0	22	1100	1 1 1 1 1 1 1 0 0 0
11	1450	1 1 1 1 1 1 1 1 1 0	23	900	1 1 0 1 0 0 0 0 0 0
12	1500	1 1 1 1 1 1 1 1 1 1	24	800	1 1 0 0 0 0 0 0 0 0

Table 3: optimal setting of Lagrangian multipliers.

Hour	Lambda (λ)	Mu (μ)	Hour	Lambda(λ)	Mu(μ)
01	17.4119	4.4492	13	22.7296	13.9088
02	17.4377	2.5	14	20.3766	8.4348
03	17.4894	5.0906	15	19.9388	5.2353
04	20.0184	4.1185	16	17.4522	6.8963
05	17.5018	6.4276	17	17.4212	6.0896
06	17.4832	4.2417	18	17.4832	9.149
07	17.5142	3.9884	19	19.9387	12.4331
08	19.9388	3.3649	20	22.7299	15
09	20.3766	10.5754	21	20.3765	5.5085
10	22.7299	14.8263	22	17.4708	7.4622
11	23.2995	13.891	23	17.4553	6.5963
12	26.2752	13.9741	24	17.4739	2.6161

VII. Conclusion:

The use of a differential evolution algorithm for the unit commitment problem is explored in this paper; the LR method is used to solve the UC problem. Optimal settings of the Lagrangian multipliers are obtained using DE algorithm. Simulations are carried out on a 10-unit test system. The performances of the different methods are compared with the proposed method. Results show the robustness of the proposed method.

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