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A New Approach Based on Variable Scaling Hybrid Differential Evolution for Unit Commitment Problem

[1]M. Ramu, [2]L. Ravi Srinivas and [2]S. Tara Kalyani
[1]Department of Electrical and Electronics Engineering,
Jawahar lal Nehru Technological University (JNTU), Hyderabad, India
[2]Department of Electrical and Electronics Engineering, Gudlavalleru Engineering College,
Gudlavalleru, India

Abstract: This study proposes a new methodology which is dependent on Variable Scaling Hybrid Differential Evolution (VSHDE) combined with Lagrangian Relaxation (LR) to solve the large scale Unit Commitment Problem (UCP). The VSHDE method holds the properties of HDE method, superseding the disadvantage caused by fixed and random scaling factors used in the HDE method, VSHDE additionally adopts, the concept of the variable scaling factor which is dependent on the 1/5 success rule of Evolution Strategies (ESs). In this study, VSHDE algorithm is used to tune the Lagrangian multipliers more effectively. The UC is decided by the LR method. The proposed method is tested on generating units ranging from ten units to hundred units and the results attained are compared with other methods to validate its viability.

Key words: Unit Commitment (UC), Hybrid Differential Evolution (HDE), Variable Scaling Hybrid Differential Evolution (VSHDE), Lagrangian multipliers, generating units, Evolution Strategies (ESs)

INTRODUCTION

Unit Commitment (UC) is a major optimization problem to fix the combination of available generating units and scheduling their respective loads (Wood and Wollenberg, 2007). UC schedule mainly aims at minimizing the fuel cost within the considered period of 24 h (a day). A number of optimizations techniques are available to solve the UCP with a period of 24 h. The UC solution aims to reduce the fuel cost, startup/shut down cost and no-load cost (Bertsimas *et al*., 2013; Bhardwaj *et al*., 2012). The past UC methods constitute of priority list method (Tingfang and Ting, 2008), dynamic programming (Snyder *et al*., 1987), Lagrangian relaxation (Ongsakul and Petcharaks, 2004). Though Lagrangian relaxation approach is being regularly used by researchers nowadays to solve the UC problem, it is more pragmatically helpful for large span of generation utility because as there is a significant growth in generating unit strength, the degree of sub optimality turns to zero and it is being simply modified to model the characteristics of specific utilities. Non-classical methods have been developed which comprise of artificial neural networks (Sendaula *et al*., 1991), Genetic algorithm (Kazarlis *et al*., 1996), simulated annealing (Simopoulos *et al*., 2006), Tabu-search method (Rajan and Mohan, 2004), fuzzy logic algorithm (Kadam *et al*., 2009), cone programming (Yuan *et al*., 2013), particle swarm optimization (Balci and Valenzuela, 2004), differential evolution (Qin *et al*., 2009; Jeong *et al*., 2009; Price *et al*., 2005), hybrid differential evolution (Chiou and Wang, 1999) and its modifications (Wong and Dong, 2005; Price, 1997; Bai *et al*., 2012), variable scaling hybrid differential evolution algorithm and its improvements (Chiou, 2007; Bdack *et al*., 1991) to solve various engineering problems. This study presents an efficient algorithm that is a Variable Scaling Hybrid Differential Evolution (VSHDE) incorporating Lagrangian relaxation method is proposed to solve the UC problem. The UC problem is computed by the LR technique whereas Lagrangian multipliers are initiated and updated by the VSHDE algorithm.

Problem formulations: The problem of unit commitment is during the 24 h time horizon to reduce the cost of production within the constrained limits of spinning reserve and operation of the generator. The objective function to be minimized is:

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

Corresponding Author: M. Ramu, Department of Electrical and Electronics Engineering,
Jawahar lal Nehru Technological University (JNTU), Hyderabad, India

Subjected to constraints; power balance as constraint:

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

Spinning reserve as constraint:

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

Generator limit constraints:

$$P_{i,min} U_{i,t} \leq P_i^t \leq P_{i,max} U_{i,t}, i = 1, ..., N \tag{4}$$

Minimum up and down time as constraints:

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

Startup cost:

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

Lagrangian relaxation: In the Lagrangian relaxation methodology, the coupling constraints will be totally by-passed during the computation of the UC problem. The passage for achieving this is the dual optimization technique (Ongsakul and Petcharaks, 2004):

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

λ^t and μ^t are non negative and minimizing λ^t and μ^t w.r.t to the other control variables in problem is:

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

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

Now Lagrangian is function rewritten as:

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

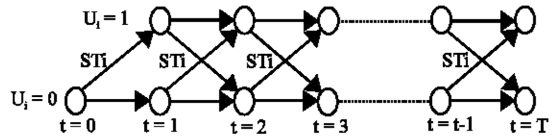

Fig. 1: DP method with two-states

By considering the individual thermal units while ignoring the coupling constraints momentarily, the below term can be reduced. So, we can easily compute LR function for individual generators $\sum_{t=1}^{T}\{[F(P_i^t)+ST_{i,t}(1-U_{i,t-1})]U_{i,t} - \lambda^t P_i^t U_{i,t} - \mu^t P_{i,max} U_{i,t}\}$ that is:

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

Subjected to $U_{i,t} P_{i,min} \leq P_i^t \leq U_{i,t} P_{i,max}$. For t = 1, 2, ..., T and constraints in Eq. 5.

On/Off decision criterion: In this LR technique each unit is considered individually for gaining the dual solution with the help of Dynamic Programming (DP). The unit 'i' having two states which are possibly true depicted in Fig. 1. Here, $U_{i,t} = 0$ state which has to be condensed is ignored and at $U_{i,t} = 1$ the minimizing function is $[F_i(P_i^t) - \lambda^t P_i^t]$. We neglect startup cost and the term $\mu^t P_{i,max}$ are go down here because minimization is with respect to P_i^t. Dual power can be calculated by the term min $[F_i(P_i^t) - \lambda^t P_i^t]$ with the help of minimize condition for population:

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

The solution to this equation is:

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

Dual power is obtained as:

$$\frac{dF_i\left(P_i^{t,\,dual}\right)}{dP_i^t} = \lambda^t \tag{14}$$

The following three cases are needed to verify $P_i^{t,opt}$ beside its limits:

- if $P_i^{t,dual} < P_{imin}$, Then the $P_i^t = P_{imin}$
- if $P_{imin} \leq P_i^{t,dual} \leq P_{imax}$, Then the $P_i^t = P_i^{t,dual}$
- if $P_i^{t,dual} > P_{imax}$, Then the $P_i^t = P_{imax}$

In order to select the feasible schedule of individual generations from the previous horizon chart, the DP is adopted for individual state and individual hour respectively. The choice of switching on/off is done by choosing the minimum cost criterion from both the start-up cost and accumulated cost of two past ways. Hence the on/off decision should be computed by using dual power solution:

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

To minimize the above term stated in Eq. 15 at individual hour, if $[F_i(P_i^t)+ST_{i,t}(1\text{-}U_{i,t\text{-}1})]U_{i,t}\text{-}\lambda^t P_i^t U_{i,t}\text{-}\mu^t P_{i,max}] \leq 0$ in order to satisfy the unit criterion, it shouldn't cross the boundaries of the minimum downtime constraint $U_{i,t} = 1$.

Overview of hybrid differential evolution: "Hybrid Differential Evolution (HDE)" is a population dependent stochastic technique. It comprises an addition from the unique DE algorithm as initiated by Price *et al.* (2005). DE is used to solve the unconstrained nonlinear optimization problems. The extension of original DE to solve the various optimization problems have introduced by Chiou and Wang (1999). The HDE involves the basic operations, they are:

- Initialization
- Mutation
- Crossover
- Selection and evaluation
- Migration

MATERIALS AND METHODS

Variable scaling hybrid differential evolution method: The VSHDE method is an improvement made for hybrid differential evolution algorithm. The local exploitation ability of DE is observed as weak and has a disability of premature convergence. The HDE algorithm has the drawback of fixed scaling factor F. The VSHDE algorithm uses the concept of variable scaling factor to overcome this problem (Chiou, 2007).

Step 1; Initialization: The initial population required for the evaluation process is produced randomly and is specified by the Eq. 16:

$$U_i^0 = U_{i,min}+rand().(U_{i,max}\text{-}U_{i,min}), i = 1, ..., n_p \quad (16)$$

Rand () represents a uniformly distributed variable number having range (0, 1). This leads to the generation of n_p number of individuals U_i^0 independently. At the time of initialization, the control variables were randomly generated, surrounded by allowable ranges.

Step 2; Mutation operation: Difference vector plays a prominent role in mutation process. The mutation process is taken from (Qin *et al.*, 2009) and is given:

$$U_i^{G+1} = U_i^G+F(U_{best}^G\text{-}U_i^G)+F(U_{r1}^G\text{-}U_{r2}^G) \quad (17)$$

Here, mutation constant is 'F'. r1, r2, r3, r4, ..., are randomly selected indices from the population, np.

Step 3; Crossover operation: The Crossover or recombination is an appreciative method for differential evolution. Its aim is to strengthen the successes rate by producing children from their present parents. In future generations for diversity expansion among individuals we use perturbed $\hat{U}_i^{G+1}$ individuals and present U_i^G individuals are selected by variable number. Individual parameter j of the i^th^ individual is reproduced from the perturbed each $\hat{U}_i^{G+1}$ and the present individual U_i^G as follows:

$$\hat{U}_{ij}^{G+1} = \begin{cases} U_{ij}^{G+1}, \text{if } rand(0,1) < CR \\ U_{ij}^{G}, \quad \text{Otherwise} \end{cases} \quad (18)$$

where, $I = 1, ..., n_p$; $j = 1, ..., n$; n = number of parameters.

Step 4; Estimation and selection: The fittest between the present and their offspring are preserved for future generations as follows:

$$U_i^{G+1} = \arg\min\{f(U_i^G), f(\hat{U}_i^{G+1})\} \quad (19)$$

$$U_b^{G+1} = \arg\min\{f(U_i^{G+1})\} \quad (20)$$

where, arg min means the argument of the minimum. Here, f is the extended objective function that has to be minimized.

Step 5; Migration operation if necessary: A migration operation is introduced for efficiency in finding the search space in order to minimize the selection weight for a smaller population. This new population which is achieved is dependent on best X_b^{G+1} individual. The j-th gene of the i-the individuals:

$$U_{ij}^{G+1} = \begin{cases} U_{bj}^{G+1} + \rho_1 (U_{jmin} - U_{bj}^{G+1}), \text{ if } \rho_2 < \dfrac{U_{ij}^{G+1} - U_{jmin}}{U_{jmax} - U_{jmin}} \\ U_{bj}^{G+1} + \rho_1 (U_{jmax} - U_{bj}^{G+1}), \quad \text{otherwise} \end{cases} \quad (21)$$

where, ρ_1, ρ_2 is variably produced numbers, uniformly distributed having range [0, 1]; I = 1, ..., N_P; j = 1, ..., n; n = number of parameters. Migration operation is proposed to carry out only if population diversity condition is not met. This measure is represented as:

$$\rho = \sum_{\substack{i=1 \\ i \neq b}}^{N_p} \sum_{j=1}^{n} \chi_{ij} / n(n_p - 1) < \varepsilon_1 \quad (22)$$

$$\chi_{ij} = \begin{cases} 1, \text{ if } \left| \dfrac{U_{ij}^{G+1} - U_{bj}^{G+1}}{U_{bj}^{G+1}} \right| > \varepsilon_2 \\ 0, \quad \text{otherwise} \end{cases} \quad (23)$$

Parameters $\varepsilon_1 \epsilon [0, 1]$ and $\varepsilon_2 \epsilon [0, 1]$ show the best individual parameters for our desired population diversity tolerance and genetic diversity. Here χ_{ij} is the index of gene diversity. Best individual gene χ_{ij} is equal to 0. Equation 17 and 18, we come to know that ρ value range is [0, 1]. Migration operation is put forth depending on value of ρ and ε_1. If ε_1 is greater than ρ, then migration is carried out for producing new population.

Step 6; Variable scaling of mutation constant (scaling factor) F: The utilization of variable scaling factor dependent on the 1/5 success rule is the primary objective of VSHDE methodology. Since, fixed scaling factor is a disadvantage in HDE technique, updating scaling factor dependent on 1/5 success rule is employed here instead. This rule is as follows:

$$F^{t+1} = \begin{cases} c_d \times F^t, \text{if } \rho_S^t < 1/5 \\ c_j \times F^t, \text{if } \rho_S^t > 1/5 \\ F^t, \quad \text{if } \rho_S^t = 1/5 \end{cases} \quad (24)$$

where, ρ_S^t is the number of successful mutations. Here a far better individual is obtained successfully than present best individual. The initial value of the scaling factor, F is set to 1.2 (Wong and Dong, 2005; Price, 1997). The factors of Cd = 0.8 and Cj = 1/0.8 are employed for adjustment which occur for every q iterations. The iteration index q is is equal to 10b where b is a constant. When the migration operation is carried out, the scaling factor is represented as:

$$F = 1 - \frac{iter}{iter_{max}} \quad (25)$$

Wheres, iter and iter max are the no. of the current iteration and the maximum iteration, respectively. And the scaling factor is reset as, if it is a far smaller value to find better solution in the solution process.

Step 7; Steps 2-6 are carried out repeatedly till maximum iteration quantity is attained

Implementation of proposed VSHDE method: Implementation starts with encoding parameters. Generators are committed in a system to meet the load requirements of the particular hour. An appropriate generator is selected naturally to make the unit commitment successful with reasonable cost. The number of base generators remains constant in each hour regardless of load variations. Different generators from system are respectively selected for meeting the load in each hour. After completion of successful iterations, a pattern is proposed. The fitness value associated with this pattern is calculated and the best value among these pattern is chosen, a feasible solution is having a minimal cost function. The fitness function to be reduced by:

$$f = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N} \left[F_i\left(P_i^T\right) + ST_{i,t}\left(1 - U_{i,t-1}\right) \right] U_{i,t} + K_s \sum \left(S_p - S_{plim}\right)^2 \right\} + K_u \sum \left(T_U - T_{ulim}\right)^2 + K_d \sum \left(T_U - T_{ulim}\right)^2 \quad (26)$$

where, k_s, k_u and k_d are the weights associate with spinning reserve, uptime and downtime constraints, respectively.

The main computational procedure of VSHDE is shown from step 1-7. The proposed method mainly involves cost effective unit commitment (selection of appropriate units) with the application of HDE and VSHDE algorithms. The computation finds better unit commitment with reduced cost.

RESULTS AND DISCUSSION

The proposed algorithm for computing the unit commitment problem was programmed in MATLAB of version 2010a environment. Test system consists of 10-100 power generating units (Kazarlis *et al*., 1996). For implementing the proposed solution the population is set to be 50 and iterations are 100.

The hybrid differential evolution and variable scaling hybrid differential methods have been tested on the 10-100 generator system. The 10 runs were carried out for each set from 10-100 generators for both HDE and VSHDE methods. The best of the runs is considered as the

Table 1: Unit commitment schedule of the VSHDE 20 generator system

Hour	Units On/Off schedule
1	11110000000000000000
2	11110000000000000000
3	11110000010000000000
4	11110000110000000000
5	11110001110000000000
6	11111011110000000000
7	11111011110000000000
8	11111111110000000000
9	11111111111110000000
10	11111111111111110000
11	11111111111111111100
12	11111111111111111111
13	11111111111111110000
14	11111111111110000000
15	11111111110000000000
16	11111111110000000000
17	11111111110000000000
18	11111111110000000000
19	11111111110000000000
20	11111111111100111110
21	11111111111100100000
22	11111001011100000001
23	11110000010000000000
24	11110000000000000000

Table 2: Unit commitment schedule of the VSHDE 40 generator systems

Hour	Units On/Off schedule
1	1111111100000000000000000000000000000000
2	1111111100000000000000000000000000000000
3	1111111100000000000100000000000000000000
4	1111111100000001011100000000000000000000
5	1111111100000011111100000000000000000000
6	1111111100011111111100000000000000000000
7	1111111100111111111100000000000000000000
8	1111111111111111111100000000000000000000
9	1111111111111111111111111000000000000000
10	1111111111111111111111111111111100000000
11	1111111111111111111111111111111111110000
12	1111111111111111111111111111111111111111
13	1111111111111111111111111111111100000000
14	1111111111111111111111111000000000000000
15	1111111111111111111100000000000000000000
16	1111111111111111111100000000000000000000
17	1111111111111111111100000000000000000000
18	1111111111111111111100000000000000000000
19	1111111111111111111100000000000000000000
20	1111111111111111111111111000111111110000
21	1111111111111111111111111000000000000000
22	1111111111000000111111111000000000000000
23	1111111100000000001100000000000000000000
24	1111111100000000000000000000000000000000

Table 3: Comparison of various methods

No. of units	Best cost ($)	Average cost($)	Worst cost ($)
10	563,966	565,921	567,730
20	1,123,555	1,125,250	1,128,110
40	2,246,803	2,250,322	2,252,703
60	3,369,534	3,372,666	3,377,654
80	4,486,242	4,491,244	4,500,174
100	5,604,622	5,614,555	5,623,808

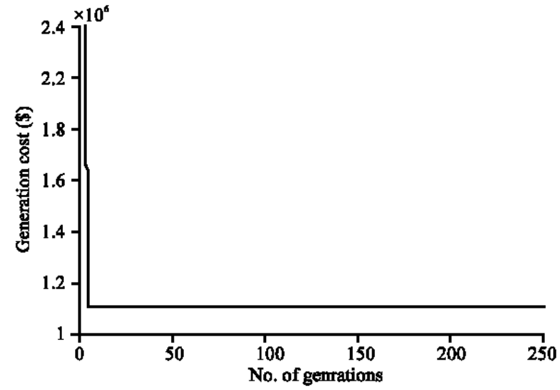

Fig. 2: Convergence of cost of 20-unit system with VSHDE algorithm

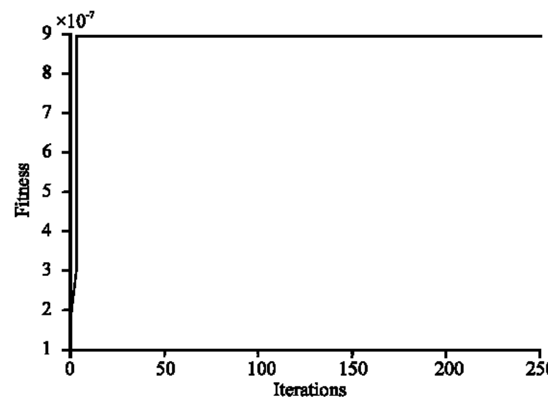

Fig. 3: Convergence of fitness of 20-unit system with VSHDE algorithm

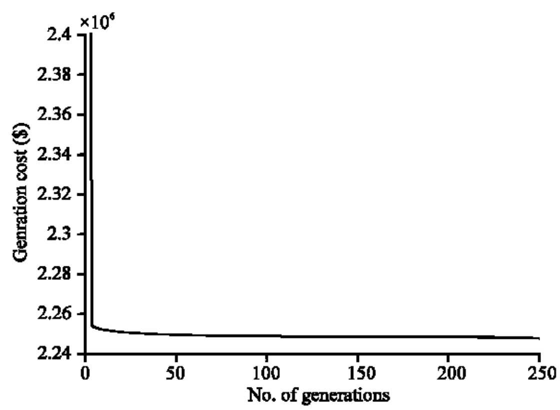

Fig. 4: Convergence of total cost of 40-unit system with VSHDE algorithm

optimum solution. Results are compared with the existing methods for verifying robustness of proposed methods. Unit commitment schedule of VSHDE algorithm for 20 and 40 generator systems are given in Table 1 and 2 respectively. Figure 2-4 show the convergence of total cost for 20-unit system and 40 unit systems, respectively of VSHDE algorithm. Comparison of results of the proposed method with other methods is given in Table 3.

Table 4: Simulation results of the proposed VSHDE method

No. of generators	Total cost ($) LR (Kazarlis *et al.*, 1996)	GA (Kazarlis *et al.*, 1996)	DPLR (Ongsakul and Petcharaks, 2004)	ALR (Ongsakul and Petcharaks, 2004)	ELR (Ongsakul and Petcharaks, 2004)	HDE	VSHDE
10	565,825	565,825	564,049	565,508	563,977	563,977	563,966
20	1,130,660	1,126,243	1,128,098	1,126,720	1,123,297	1,123,921	1,123,297
40	2,258,503	2,251,911	2,256,195	2,249,790	2,244,237	2,246,821	2,243,363
60	3,394,066	3,376,625	3,384,293	3,371,188	3,363,491	3,370,001	3,369,534
80	4,526,022	4,504,933	4,512,391	4,494,487	4,485,633	4,494,279	4,486,242
100	5,657,277	5,627,437	5,640,488	5,640,488	5,605,678	5,605,561	5,604,951

Table 5: Executed time (sec) for VSHDE

No. of units	VSHDE average execution time (sec)
10	12.18
20	13.75
40	24.22
60	34.41
80	51.38
100	81.04

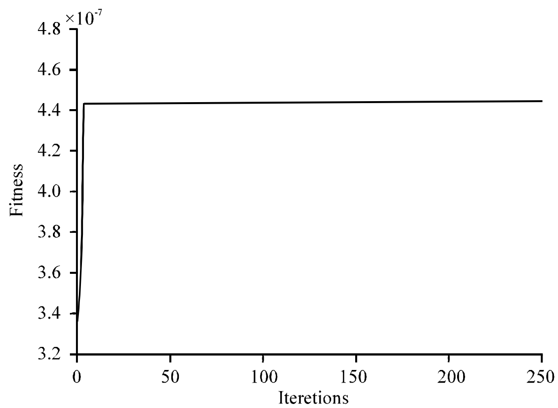

Fig. 5: Convergence of fitness of 40-unit system with VSHDE algorithm

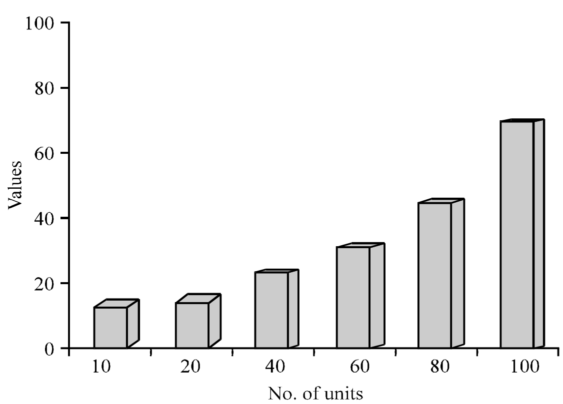

Fig. 6: Variation of execution time (10-100 units) VSHDE method

Simulation results of the proposed VSHDE method and execution time (sec) for VSHDE is given in Table 4 and 5 respectively. Figure 5 and 6 show the fitness of UC solution for 10 and 40 unit systems.

CONCLUSION

This study proposes new methods using hybrid differential evolution and Variable Scaling Hybrid Differential Evolution (VSHDE) optimization algorithms for finding the solution for UC problem. The total production costs over the schedule of 24 h horizon by HDE and VSHDE algorithms are reduced when compared with other optimization methods. Simulation results demonstrate the robustness of the proposed method.

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

k = Iteration counter

N = Total number of generator units

$P_{i, min}$ = Minimum real power generation of unit i (MW)

$P_{i, mix}$ = Maximum real power generation of unit i (MW)

P_i^t = Real power generation of unit i at hour t (MW)

$P_{i,opt}^t$ = Optimal generation output of unit i at hour t (MW)

P_D^t = Load demand at hour t (MW)

R^t = Spinning reserve at hour t (MW)

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 (h)

$T_{i, down}$ = Minimum down time of unit i (h)

$T_{i, off}$ = Continuously off time of unit i (h)

$T_{i, on}$ = Continuously on time of unit i (h)

$T_{i, up}$ = Minimum up time of unit i (h)

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

$\lambda^{t(k)}, \mu^{t(0)}$ = Initial Lagrangian multiplier at hour t (units/mh, units/MW)

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

Y_i^{G+1} = Perturbed individual

X_i^G = Present individual

F = Mutation constant

n_C = Dimension of decision parameters

Cr = Crossover constant
x_B^{G+1} = Best individual
X_{ij} = Index of the gene diversity
ε_1, ε_2 = Desired tolerance for the population diversity and the gene diversity with respect to the best individual

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