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Multi-Objective Unit Commitment Using Adaptive Teaching Learning Based Optimization

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ABSTRACT

Unit Commitment determines on/off status of generating units that minimizes the generation cost. Operating at absolute minimum generation cost can no longer be the only criterion for dispatching electric power as it poses increasing concern over environmental considerations. This paper presents an adaptive teaching learning based solution methodology for unit commitment with a goal of simultaneously minimizing only the generation cost and emissions. The algorithm adoptively adjusts the teaching factor in tune with the performance function. Numerical results on systems up to 100 generating units demonstrate the effectiveness of the proposed strategy.

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Nomenclature:

CST_i Cold startup cost of unit i ($)
UC Unit commitment
TLBO Teaching learning based optimization
ATLBO Adaptive TLBO
a, b, c Fuel cost coefficients
d, e, f Emission coefficients
$E_i(P_{Gi}^k)$ Emission function (lb/h)
$F_i(P_{Gi}^k)$ Generator fuel cost function ($/h)
$\Phi_{FE}(P_G, U)$ Objective function to be minimized over the scheduling period
HST_i Hot startup cost of unit *i* ($)
$iter^{\max}$ Maximum number of iterations
N Total number of generating units
$P_{Gi}^{\max}$ Maximum real power generation of unit i (MW)
$P_{Gi}^{\min}$ Minimum real power generation of unit i (MW)
$P^t{}_i$ Generation output power of unit i at k-th interval (MW)
P_D^k Load demand at *k*-th interval (MW)
$PI^{i,t}$ Performance index of i -th student at t-th iteration
$PI^{teacher,t}$ Performance index of the teacher at t-th iteration
R^k Spinning reserve at *k*-th interval (MW)
$rand$ A random number generated in the range [0,1]
ST_i^k Startup cost of unit *i* at *k*-th interval ($)
T Total number of hours
T_i^{cold} Cold start hour of unit *i* (hours)
T_i^{down} Minimum down time of unit *i* (hours)
T_i^{off} Continuously off time of unit *i* (hours)
T_i^{on} Continuously on time of unit- *i* (hours)
T_i^{up} Minimum up time of unit- *i* (hours)
$t_f^{i,t}$ Teaching factor of i -th student at t-th iteration
$U_{i,k}$ Status of unit- i at k-th interval $(on = 1, off = 0)$

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INTRODUCTION

Unit Commitment (UC) is an important computational process in the daily operation and planning of power system. It determines the optimal scheduling of the generating units along with their generation levels at minimum operating costs while satisfying the system and unit constraints. It can be formulated as a non-linear, large-scale, mixed-integer combinatorial optimization problem, which is quite difficult due to its inherent high dimensional, non-convex, discrete and nonlinear nature. Besides, the dimension of the problem increases rapidly with the system size and the scheduling horizon (Wood, A.J. and B.F. Wollenberg, 1996).

The fossil fuel based power plants emit several contaminants and greenhouse gases that pollute the atmosphere and cause global warming as well. There is thus a need for effective techniques that reduce the pollutants with a view of keeping the air clean and reducing the effects of global warming. Many strategies like installing post-combustion cleaning equipment, changing fuel type to fuel with less pollutants, or dispatching with minimum emissions have been suggested recently (Lamont, J.W. and E.V. Obessis, 1995). The latter option is preferred in many cases due to economic reasons since no capital cost is needed and its immediate availability for short term operation. The UC problem becomes a multi-objective problem with conflicting objectives since emission minimization conflicts with fuel cost minimization.

Several methods have been suggested for UC problems in the recent decades. At one end of the spectrum, there are simple and fast but highly heuristic priority list (Baldwin, C.J., 1960) methods. At the other end, there are dynamic programming (Snyder, W.L., 1987; Hobbs, W.J., 1982) and branch-and bound (Dillon, T.S.; Cohen, A.I., M. Yoshimura, 1983), which are in general, flexible, but often prone to the curse of dimensionality. Between the two extremes, there are Lagrangian relaxation (LR) methods (Lee, F.N., 1989; Cheng, C.P., 2000), which are efficient and appear to be a desirable compromise, and well suited for large-scale UC. However under certain constraints such as crew constraints, these methods demand additional heuristics detrimental to efficiency of the method.

Nature inspired optimization methods such as genetic algorithms [10] simulated annealing (Mantawy, A.H., 1988) and evolutionary programming (Juste, K.A., 1999) have been applied in solving UC problems in the recent years with a view of overcoming the drawbacks of classical approaches. Recently, a population based Teaching-Learning-Based Optimization (TLBO) algorithm that works on the effect of influence of a teacher on the output of learners in a class room has been outlined by Rao *et al* (2011,2012) for solving multimodal optimization problems. It is an algorithm-specific parameter-less algorithm, as it requires only common controlling parameters like population size and number of generations for its working. Since its introduction, it has been applied to a variety of problems including parameter optimization of modern machining processes (Rao, R.V. and V.D. Kalyankar, 2013), optimal reactive power flow (Barun Mandal and Provas Kumar Roy, 2013) and optimal power flow (Amin Shabanpour-Haghighi, 2014) and found to yield satisfactory results.

This paper aims to develop an elegant method for solving multi-objective UC problem using ATLBO. Results on test systems up to 100 generating units are presented to showcase the effectiveness of the developed method.

Problem Description:

The main objective of UC problem is to minimize the overall emissions of all the generating units over the scheduled time horizon under the spinning reserve and operational constraints of generator units. This constrained optimization problem is formulated as

Minimize

$$\Phi_{FE}(P_G,U)=\sum_{k=1}^{T}\sum_{i=1}^{N}\left\{\omega\,F_i(P_{Gi}^k)+(1-\omega)h^k\,E_i(P_{Gi}^k)+ST_i^{\,k}\left(1-U_{i,k-1}\right)\right\}U_{i,k} \quad (1)$$

Subject to,

Power balance constraint:

$$P_D^k-\sum_{i=1}^{N}P_{Gi}^k\,U_{i,k}=0 \quad (2)$$

Spinning reserve constraint:

$$P_D^k+R^k-\sum_{i=1}^{N}P_{Gi}^{\ \max}\,U_{i,k}\le 0 \quad (3)$$

Generation limit constraints:

$$P_{Gi}^{\ \min}U_{i,k}\le P_{Gi}^k\le P_{Gi}^{\ \max}U_{i,k} \qquad i=1,2,\cdots,N \quad (4)$$

Minimum up and down time constraints:

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

Start-up Cost:

$$ST_i=\begin{cases}HST_i & if\ T_i^{down}\le T_i^{off}\le T_i^{cold}+T_i^{down}\\ CST_i & if\ T_i^{off}>T_i^{cold}+T_i^{down}\end{cases} \quad (6)$$

Where,

$$F_i(P_{Gi}^k)=a_iP_{Gi}^{k\,2}+b_iP_{Gi}^k+c_i \quad (7)$$

$$E_i(P_{Gi}^k)=d_iP_{Gi}^{k\,2}+e_iP_{Gi}^k+f_i \quad (8)$$

3. TLBO:

TLBO, inspired from teaching–learning process in class rooms, is suggested for solving multimodal optimization problems. In this approach, each student comprising grade points of different subjects represents a solution point and his/her performance is analogous to fitness value of the problem. The best student in the population is considered as the teacher. A group of students comprising a teacher forms the population and the solution process is governed by two basic operations, namely teaching and learning phases, which are briefed below:

Teaching Phase:

The teaching phase represents the global search property of the TLBO algorithm. During this phase, the teacher, who is the most experienced and knowledgeable person in the class, imparts knowledge to all the students with a view of improving the performance of the whole class from initial level to his own level. The teaching increases the mean grade point of the subject. The change in the grade point of the student can be expressed as

$$\Delta S^{j\,t} = rand(0,1)\times\left(S^{j\,t}_{teacher} - t_f\ S^{j\,t\,ave}\right) \tag{9}$$

Where,

$S^{j\,t\,ave}$ is the mean grade of the j-th subject at t-th iteration and computed by

$$S^{j\,t\,ave} = \frac{1}{nS}\sum_{i=1}^{nS} S_i^{j\,t} \tag{10}$$

$S^{j\,t}_{teacher}$ is the grade point of the j-th subject of the teacher at t-th iteration

t_f is the teaching factor, which decides the value of mean to be changed and can be either 1 or 2, evaluated by

$$t_f = round([1+rand(0,1)\{1,2\}] \tag{11}$$

The new grade point of the j-th subject of the i-th student, as a result of teaching, is mathematically modeled by

$$S_i^{j\,t+1} = S_i^{j\,t} + \Delta S^{j\,t} \tag{12}$$

The grade points of all the students at the teaching phase are further improved by the learning phase.

Learning Phase:

In this phase, the students enrich their knowledge by interaction among themselves, which helps in improving their performances. The influence on the grade points due to the interaction of p-th student with q-th student may be mathematically expressed as follows:

$$S_p^{j\,t+1} = \begin{cases} S_p^{j\,t} + rand\times\left(S_p^{j\,t} - S_q^{j\,t}\right) & if\ PI_p > PI_q \\ S_p^{j\,t} + rand\times\left(S_q^{j\,t} - S_p^{j\,t}\right) & if\ PI_p < PI_q \end{cases} \tag{13}$$

PI_p and PI_q is the performance, indicating the fitness, of the p-th and q-th student respectively.

4. Adaptive tlbo:

The teaching factor of TLBO, narrated in section 3, decides the value of mean to be changed. It is adaptively modified at *t*-th iteration as.

$$t_f^{i,t} = \begin{cases} \dfrac{PI^{i,t}}{PI^{teacher,t}} & if\ PI^{teacher,t} \neq 0 \\ 1 & otherwise \end{cases} \tag{14}$$

It does not require the factor to be specified at the beginning of the optimization process. The TLBO with adaptive mechanism is hereafter represented as adaptive TLBO (ATLBO) throughout the thesis.

5. Proposed method:

The proposed method (PM) uses ATLBO with a goal of enhancing the search process, improving the computational efficiency and obtaining the global best solution for UC problem with emissions. It also involves the representation of problem variables and formation of a performance index (PI) function.

5.1. Representation of Grade Points:

The grade points S of each student in the PM is represented to denote the binary UC variable, $U_{i,t}$, which represents on/off status of unit- i at hour-t chosen primary design variables in matrix form as shown in Fig. 1.

		1	2	……	N
	1	$U_{1,1}$	$U_{1,2}$	……	$U_{1,T}$
	2	$U_{2,1}$	$U_{2,2}$	……	$U_{2,T}$
S =	. .	. .	. .	. .	. .
	T	$U_{N,1}$	$U_{N,2}$	……	$U_{N,T}$

Fig. 1: Representation of a student.

5.2. Binary Conversion Mechanism:

The binary conversion mechanism, suggested by Kennedy and Eberhart [20] for PSO, enables the algorithm to operate in binary spaces. The same mechanism can be employed in the ATLBO for converting the real valued grade points of the students in the population into binary 0's and 1's as outlined below.

$$S_p^{j\,t+1} = \begin{cases} 1 & if\ B^T < G\left(S_p^{j\,t+1}\right) \\ 0 & otherwise \end{cases} \tag{15}$$

Where,

$$G\left(S_p^{j\,t+1}\right) = \frac{1}{1+\exp\left(-S_p^{j\,t+1}\right)} \tag{16}$$

5.3. Repair Algorithm:

Spinning reserve, minimum up/down time constraints are important in UC problems. During iterative process, these constraints are often violated and the system may suffer from deficiency in units. At this stage, a repair algorithm can enhance the solution process. The proposed repair algorithm is outlined below.

1. If spinning reserve constraint is not satisfied, randomly change an off status unit to on $(0 \rightarrow 1)$.
2. If the net minimum power generation of on status units is greater than the power demand, randomly change an on status unit to off $(1 \rightarrow 0)$.
3. If minimum up/down time constraint is violated, identify the stream of bits that causes violation and alter them in order to overcome this violation. For example a string of 1111001111 may be modified either as 1111111111 or 1110001111 or 1111000111. However, the one that requires least bit changes is chosen for repair.
4. Repeat steps 1-3 till all the constraints are satisfied.

5.4. Non-iterative Technique for EED:

The EED is an intensive computational part in UC problem. It is solved using a time consuming λ iteration method based on the principle of equal incremental cost as the fuel cost is represented by a quadratic cost function. The PM uses a non-iterative EED (Palanichamy, C. and N. Sundar Babu, 2008) in order to improve the computational speed.

Based on the bi-objective function of EED, the fuel cost and emission coefficients are combined as

$$a'_i = \omega a_i + (1-\omega) h\, d_i$$
$$b'_i = \omega b_i + (1-\omega) h\, e_i \qquad (17)$$
$$c'_i = \omega c_i + (1-\omega) h\, f_i$$

The co-ordination equation of the conventional $\lambda -$ iteration method at interval-k can be written as,

$$\frac{\partial F_{ik}}{\partial P_{Gik}} = 2a'_i P_{Gi}^k + b'_i = \lambda_k \quad ; \qquad i = 1,2....N \qquad (18)$$

Rearranging Eq. (18) for optimal generations,

$$P_{Gi}^k = \frac{\lambda_k - b'_i}{2a'_i}$$

(19)

The above equation can be written in terms of P_D^k as

$$P_{Gi}^k = \frac{P_D^k - \rho - b'_i \sigma}{2a'_i \sigma} \qquad (20)$$

Where,

$$\rho = \sum_{i=1}^{N} \frac{b'_i}{2a'_i} \qquad (21)$$

$$\sigma = \sum_{i=1}^{N} \frac{1}{2a'_i} \qquad (22)$$

Eq. (17) provides optimal generations that minimizes bi-objective function of Eq. (1). Substituting Eq. (17) in Eq. (1) and rearranging

$$Min \quad \Phi_{F,k}(P_G) = A_k P_D^{k^2} + B_k P_D^k + C_k \qquad (23)$$

Where,

$$A = \sum_{i=1}^{N} \frac{1}{4a'_i \sigma^2} \qquad (24)$$

$$B = \sum_{i=1}^{N} \frac{\rho}{2a'_i \sigma^2} \qquad (25)$$

$$C = \sum_{i=1}^{N} \left(\frac{1}{4a'_i}\right)\left(\frac{\rho^2}{\sigma^2} - b'^2_i\right) + c'_i \qquad (26)$$

The demand P_D^k must be supplied by all the generating plants, that is,

$$P_G^k = \sum_{i=1}^{N} P_{Gi}^k = P_D^k \qquad (27)$$

Replacing P_{Dk} by P_{Gk} in Eq. (23)

$$\Phi_{F,k}(P_G) = A_k P_G^{k^2} + B_k P_G^k + C_k \qquad (28)$$

Differentiating and equating Eq. (28) to zero yields the optimal λ that minimizes $\Phi_{F,k}(P_G)$.

$$\lambda^o = \frac{\partial \Phi_{F,k}(P_G)}{\partial P_G^k} = 2A_k P_G^k + B_k \qquad (29)$$

The individual unit generation can be obtained by

$$P_{Gi}^k = \frac{\lambda^o - b'_i}{2a'_i} \quad i = 1,2,\cdots,N \qquad (30)$$

The algorithm is obtained below:

- Read the system data
- Calculate the cost coefficients a'_i, b'_i and c'_i
- Evaluate the constants ρ, σ, A, B and C
- Evaluate λ^o using Eq. (29) and then solve Eq. (30) for all generating plants at all intervals
- Stop

5.5 Performance Index Function:

The algorithm searches for optimal solution by maximizing a PI function, which is formulated from the objective function of Eq. (1). The performance index function is written as

Maximize

$$PI = \frac{1}{1 + \Phi_E(P_G, U)} \qquad (14)$$

5.6 Solution Process:

An initial population of students is obtained by generating random values within their respective limits to every individual in the population. The PI is calculated by considering grade points of each student; and the teaching and learning phases are performed for all the students in the population with a view of maximizing their performances. The iterative process is continued till convergence.

6. Simulation Results:

The PM has been tested on systems with 10, 20, 40, 60, 80 and 100 generating units. The unit data and load demand data for 24 hours for the system with 10 units are available in (Kazarlis, S.A., 1996). The emission coefficients are taken from (Yan-Fu Li, 2013). The data for other larger systems are obtained by duplicating the data of 10 unit system and adjusting the load demand in proportion to the system size. The population size is chosen as 30 for all the test problems. The maximum number of generations for convergence check is taken as 200, 300, 500, 700, 900 and 1000 for 10, 20, 40, 60, 80 and 100 unit systems respectively. The spinning reserve requirements are assumed to be 10% of the load demand.

Table 1: UC Schedule over scheduling horizon for 10 unit system by PM.

		Unit										Fuel Cost $/h	Emissions lb/h
		1	2	3	4	5	6	7	8	9	10		
Interval	1	1	1	0	0	0	0	0	0	0	0	13765.138	855.823
	2	1	1	0	0	0	1	0	0	0	0	15451.540	843.594
	3	1	1	0	0	0	1	0	0	0	0	17152.805	1123.644
	4	1	1	0	1	0	1	0	0	0	0	19502.672	1119.074
	5	1	1	0	1	0	1	0	0	0	0	20354.191	1269.449
	6	1	1	0	1	1	1	0	0	0	0	23044.302	1261.867
	7	1	1	0	1	1	1	0	0	0	0	23895.588	1409.482
	8	1	1	1	1	1	1	0	0	0	0	25425.807	1404.924
	9	1	1	1	1	1	1	1	0	0	0	28159.287	1794.062
	10	1	1	1	1	1	1	1	1	0	0	31046.975	2181.673
	11	1	1	1	1	1	1	1	1	1	0	33124.753	2441.024
	12	1	1	1	1	1	1	1	1	1	1	35219.489	2712.841
	13	1	1	1	1	1	1	1	1	0	0	31046.975	2181.673
	14	1	1	1	1	1	1	0	0	1	0	28335.822	1809.167
	15	1	1	1	1	1	1	0	0	0	0	25425.807	1404.924
	16	1	1	1	1	1	1	0	0	0	0	22754.855	1067.494
	17	1	1	1	1	1	1	0	0	0	0	21806.008	979.677
	18	1	1	1	1	1	1	0	0	0	0	23670.929	1167.116
	19	1	1	1	1	1	1	0	0	0	0	25425.807	1404.924
	20	1	1	1	1	1	1	0	0	0	0	32411.836	2328.897
	21	1	1	1	1	1	1	0	0	0	0	28281.203	1788.623
	22	1	1	1	1	1	1	0	0	0	0	23044.302	1261.867
	23	1	1	0	0	0	1	0	0	0	0	18004.916	1280.918
	24	1	1	0	0	0	0	0	0	0	0	15467.586	1149.673
StartUp Cost												4540.000	---
Net Fuel Cost ($/h) / Net Emissions (lb/h)												586358.593	36242.409

The detailed results comprising UC schedule, generation cost and net emissions for 10-unit system, obtained by PM, are presented in Table 1. The generation of UC schedule over the scheduling horizon are shown in Fig. 2. The net fuel cost, start-up cost and net emissions for 10, 20, 40, 60, 80 and 100 unit systems of the PM are given in Table 2.

Conclusions:

An elegant algorithm involving ATLBO for solving multi-objective UC has been proposed. The method uses a new mechanism for converting real values into binary besides adaptively adjusting the teaching factor. The repairing strategy has ensured feasible solution in the population. The method has employed a non-iterative EED that reduces the computational burden during the ATLBO iterations. The results on various test systems have clearly exhibited the superior performance of the PM and indicated that the method is ideally suitable for practical applications.

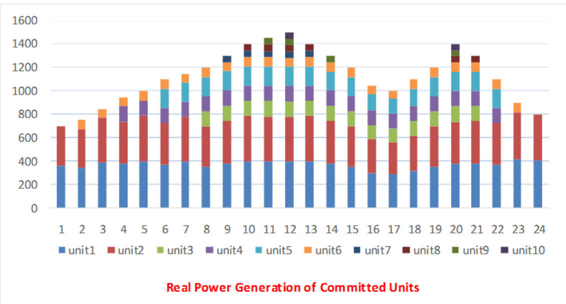

Fig. 2: Generation of Committed Units for 10 unit system by PM.

Table 2: Results of the PM.

Units	Fuel cost	Startup cost	Net cost	Net Emission
10	581818.59	4540.00	586358.59	36242.40
20	1157131.87	7620.00	1164751.87	73465.07
40	2302520.400	15000.00	2317520.40	144228.01
60	3452338.03	22380.00	3474718.03	216086.27
80	4596095.85	29880.00	4625975.85	290110.55
100	5725227.00	37320.00	5762547.00	367393.12

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