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Adaptive Teaching Learning Based Strategy for Unit Commitment with Emissions

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Abstract

The generation of electricity from fossil fuel releases several contaminants such as sulphur dioxides, nitrogen oxides and carbon dioxide into the atmosphere. The environmental awareness led to impose rigid environmental policies such as “US Clean air amendments of 1990” on power utilities to minimize the emissions. This paper presents an adaptive teaching learning based solution technique for unit commitment with an objective of minimizing the 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.

Key Words: Unit commitment, teaching learning based optimization, lambda iteration method.

Nomenclature

CST_i	Cold startup cost of unit i (\$)
UC	Unit Commitment
TLBO	Teaching learning based optimization
ATLBO	Adaptive TLBO
d,e,f	Emission coefficients
$E_i(P_{Gi}^k)$	Emission function (lb/h)
$\Phi_F(P_G, U)$	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 $(on = 1, off = 0)$

1. INTRODUCTION

Unit Commitment (UC) is another 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. The decision variables include the binary UC variables and variables associated with real power generating. The UC variables describe the ON/OFF status while the real variables indicate the generation levels of the generators at each hour of the planning period. Thus, the UC problem 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 [1].

The generation of electricity from fossil fuel releases several contaminants such as sulphur dioxides, nitrogen oxides and carbon dioxide into the atmosphere. In the past few decades, environmental awareness led to impose rigid environmental policies such as “US Clean air amendments of 1990” on power utilities to minimize their emissions. A host of strategies are in vogue to reduce power plant emissions like installing post-combustion cleaning equipment, switching to low emission fuels and replacement of the aged fuel burners or dispatching with emission considerations. The latter option is preferred in many cases due to economic reasons and its immediate availability for short-term operation. However, the other alternatives are considered as a long term option as they incur additional capital cost [2].

Many methods with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics, have been suggested in the literature. At one end of the spectrum, there are simple and fast but highly heuristic priority list [3] methods. At the other end, there are dynamic programming [4,5] and branch-and bound [6,7], which are in general, flexible, but often prone to the curse of dimensionality. Between the two extremes, there are Lagrangian relaxation (LR) methods [8,9], 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.

Meta-heuristic methods such as genetic algorithms [10] simulated annealing [11] and evolutionary programming [12] have been considered for the solution of UC 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 [13-15] 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 [16], optimal reactive power flow [17] and optimal power flow [18] and found to yield satisfactory results.

This paper aims to develop an adaptive TLBO (ATLBO) method for solving UC problem with an objective of minimizing only the emissions the developed method adaptively adjusts its parameter. The proposed method (PM) has been applied on six test systems with a view to demonstrate its performance.

2. 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 $$\Phi_E(P_G,U)=\sum_{k=1}^{T}\sum_{i=1}^{N}\left\{E_i(P_{Gi}^k)+ST_i^k\left(1-U_{i,k-1}\right)\right\}U_{i,k} \quad (1)$$

Subject to,

Power balance constraint:

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

Spinning reserve constraint:

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

Generation limit constraints:

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

Minimum up and down time constraints:

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

Start-up Cost:

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

Where,

$$E_i(P_{Gi}^k) = d_i {P_{Gi}^k}^2 + e_i P_{Gi}^k + f_i \tag{7}$$

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

$$\Delta S^{j\,t} = rand(0,1) \times \left(S_{teacher}^{j\,t} - t_f \; S^{j\,t\,ave} \right) \tag{8}$$

Where

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

$$S^{j\,t\,ave} = \frac{1}{nS} \sum_{i=1}^{nS} S_i^{j\,t} \tag{9}$$

$S_{teacher}^{j\,t}$ 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

$$t_f = round\,([1 + rand\,(0,1)\{1,2\}] \tag{10}$$

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

$$S_i^{j\,t+1} = S_i^{j\,t} + \Delta S^{j\,t} \tag{11}$$

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:

$$S_p^{j\,t+1} = \begin{cases} S_p^{j\,t} + rand \times \left(S_p^{j\,t} - S_q^{j\,t}\right) & if\ PI_p > PI_q \\ S_p^{j\,t} + rand \times \left(S_q^{j\,t} - S_p^{j\,t}\right) & if\ PI_p < PI_q \end{cases} \tag{12}$$

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 [19]

$$t_f^{i,t} = \begin{cases} \dfrac{PI^{i,t}}{PI^{teacher,t}} & if\ PI^{teacher,t} \neq 0 \\ 1 & otherwise \end{cases} \tag{13}$$

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 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 *i*-th unit at *k*-th interval in matrix form as shown in Fig. 1.

$$S = \begin{array}{c|c|c|c|c|} & 1 & 2 & \ldots\ldots & \mathrm{N} \\ \hline 1 & U_{1,1} & U_{1,2} & \ldots\ldots & U_{1,\mathrm{T}} \\ \hline 2 & U_{2,1} & U_{2,2} & \ldots\ldots & U_{2,\mathrm{T}} \\ \hline . & . & . & . & . \\ . & . & . & . & . \\ \hline \mathrm{T} & U_{\mathrm{N},1} & U_{\mathrm{N},2} & \ldots\ldots & U_{\mathrm{N,T}} \\ \hline \end{array}$$

Fig. 1 Representation of a student

5.2 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

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

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 [20]. The emission coefficients are taken from [21]. 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. For each case, totally 50 trials are performed to verify the robustness of the PM.

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

		Unit										Emissions lb/h
		1	2	3	4	5	6	7	8	9	10	
I	1	1	1	0	1	1	1	0	0	0	0	475.62
N	2	1	1	0	1	1	1	0	0	0	0	541.44
T	3	1	1	0	1	1	1	0	0	0	0	695.37
E	4	1	1	1	1	1	1	0	0	0	0	856.88
R	5	1	1	1	1	1	1	0	0	0	0	948.31
V	6	1	1	1	1	1	1	0	0	0	0	1156.9
al	7	1	1	1	1	1	1	0	0	0	0	1274.9
	8	1	1	1	1	1	1	0	0	0	0	1404.1
	9	1	1	1	1	1	1	1	0	0	0	1771.6
	10	1	1	1	1	1	1	1	1	0	0	2159.3
	11	1	1	1	1	1	1	1	1	1	0	2417.5
	12	1	1	1	1	1	1	1	1	1	1	2685.4
	13	1	1	1	1	1	1	1	1	0	0	2159.3
	14	1	1	1	1	1	1	1	0	0	0	1771.6
	15	1	1	1	1	1	1	0	0	0	0	1404.1
	16	1	1	1	1	1	1	0	0	0	0	1048.4
	17	1	1	1	1	1	1	0	0	0	0	948.31
	18	1	1	1	1	1	1	0	0	0	0	1156.9
	19	1	1	1	1	1	1	1	0	0	0	1510.8
	20	1	1	1	1	1	1	1	1	0	0	2159.3
	21	1	1	1	1	1	1	1	0	0	0	1771.6
	22	1	1	1	1	1	1	0	0	0	0	1156.9
	23	1	1	1	1	1	1	0	0	0	0	773.46
	24	1	1	1	1	1	1	0	0	0	0	625.16
Net Emissions												32872.500

The detailed results comprising UC schedule 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 emissions for 10, 20, 40, 60, 80 and 100 unit systems of the PM are given in Table 2. The best, worst and the average emissions are presented in Table 3 for 10 and 100 unit systems. This table also comprises results of the method available in [21] with a view of demonstrating the effectiveness of the PM. Analyzing the results for 10-unit system, it is very clear that the PM offers the lowest emissions of 32872.50 lb/h compared to that of the method presented in [21]. The mechanism permits the system to offer the desired amount of power with smaller emissions, even smaller than that of the existing technique. It is very clear from this table that PM produces comparatively lower emissions than those of the existing approach, thereby ensuring that the PM is able to produce the global best solution.

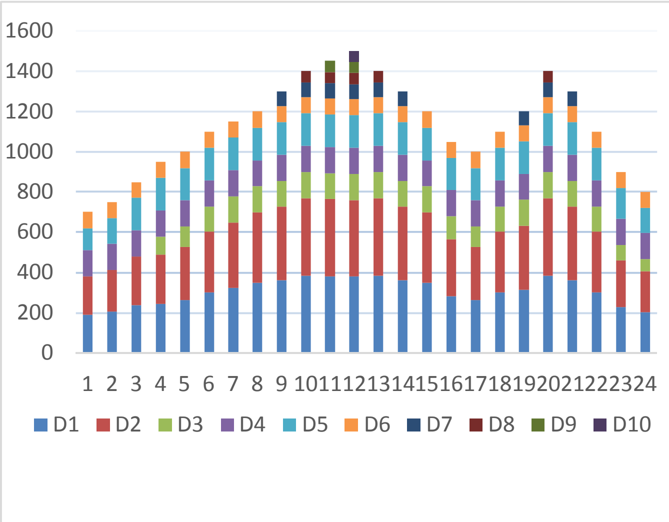

Fig.2 Generation of Committed Units for 10 unit system by PM

Table 2 Emissions of all test systems by PM

Units	Net Emission *lb/h*
10	32872.500348
20	65513.164896
40	130773.588955
60	195689.171817
80	260862.040743
100	326410.540027

Table 3 Comparison of Results for 10 and 100 unit systems

Test System	Method	Best	Worst	Average
10-units	MEO [21]	33062.00	34070	33529
	PM	32872.50	33716	33103
100-units	MEO [21]	329938.00	344560	341065
	PM	326410.54	337653	326926

7. CONCLUSIONS

A new algorithm involving ATLBO for UC with an objective of minimizing the emissions has been presented. It has been tailored to adaptively control the teaching factor so as to enhance the search process. 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.

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REFERENCES

1. A.J. Wood and B.F. Wollenberg, "Power generation, operation and control", John Wiley and sons, New York, 1996.
2. Lamont. JW and Obessis. EV. (1995). Emission dispatch models and algorithms for the 1990's, IEEE Trans. on Power Systems, 10(2), 941-946.
3. Baldwin, C.J. K.M. Dale, R.F. Dittrich, "A study of econmic shutdown of generating units in daily dispatch," AIEE Tr on PAS, Vol 78, 1960, pp 1272-1284.
4. W.L. Snyder, H.D Powell, Jr., J.C. Rayburn Dynamic programming Approach to unit commitment, " IEEE Transactions on power systems, Vol PWRS S-2, No. 2, May 1987, pp. 339-350.
5. W.J. Hobbs, G. Hermon, S. Warner, G.B. Sheble, "An Enhanced Dynamic programming Approach for unit commitment," IEEE Trans. on PAS, Vol. PAS 101, pp 79-86, January 1982.
6. T.S. Dillon, "Integer Programming Approach to the problem of optimal unit commitment with probabilistic reserve Determination," IEEE Trans. on PAS, Vol. PAS-97
7. A.I. Cohen, M.Yoshimura, "A Branch and Bound Algorithm for unit commitment, "IEEE Trans. on PAS, Vol. PAS-102, pp. 444-451, Feb 1983.
8. F.N. Lee," A Fuel-constrained unit commitment method," IEEE Transactions on Power system, Vol. 4, No3, August 1989, pp 691-698.
9. C.P. Cheng, C.W. Liu and C.C. Liu, " Unit commitment by Lagrangian Relaxation and genetic algorithem", IEEE Trans. Power Syst., Vol 15, pp 707-714, May 2000.
10. H.Tyang, P.C. Yang, and C.L. Huang, "Evolutionary Programming based economic dispatch for units with nosmooth fuel cost functions", IEEE Trans Power syst., Vol 11, pp. 112-117, feb, 1996.
11. A.H. Mantawy, Y.L. Abdel-Magid and S.Z. Selim, "A Simulated annealing algorithm for unit commitment", IEEE Trans. Power. Syst. Vol. 13, pp. 197-204, Feb. 1998.
12. K.A. Juste, H. Kita, E. Tanaka and J. Hasegawa, "An evolutionary programming solution to the unit commitment problem", IEEE Trans. Power Syst., Vol 14, pp. 1452-1459, Nov. 1999.
13. Rao. R.V, Savsani. V.J and Vakharia D.P. (2011). Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems, Computer Aided Design, 43(3): 303-315.

14. Rao. R.V, Savsani. V.J and Vakharia D.P. (2012). Teaching-learning-based optimization: A novel optimization method for continuous non-linear large scale problems, Information Sciences, 183 (1): 1-15.
15. Rao. R.V and Patel. V. (2012). An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems, International Journal of Industrial Engineering Computations, 3: 535-560.
16. Rao. R.V and Kalyankar. V.D. (2013). Parameter optimization of modern machining processes using teaching-learning-based optimization algorithm, Engineering Applications of Artificial Intelligence, 26: 524-531.
17. Barun Mandal and Provas Kumar Roy. (2013). Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization, Electrical Power and Energy Systems 53: 123-134.
18. Amin Shabanpour-Haghighi, Ali Reza Seifi and Taher Niknam. (2014). A modified teaching-learning based optimization for multi-objective optimal power flow problem, Energy Conversion and Management, 77: 597-607.
19. Rao. R.V and Patel. V. (2013). An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems, Scientia Iranica, 20(3): 710-720.
20. S.A. Kazarlis, A.G. Bakirtzis and V. Petidis, “A genetic algorithm solution to unit commitment problem”, IEEE Trans. Power Syst., Vol 11, pp.83-92, Feb. 1996.
21. Yan-Fu Li, Member, Nicola Pedroni, and Enrico Zio. (2013). a memetic evolutionary multi-objective optimization method for environmental power unit commitment, IEEE Trans on Pow Syst., 28(3): 2660-69.