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Best Compromised Schedule for Multi-Objective Unit Commitment Problems

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Abstract

The paper attempts to develop a methodology to obtain Best Compromised Schedule (BCS) of Multi-Objective Unit Commitment (UC) Problem. The UC Problem is formulated to minimize both the fuel cost and Emission. The traditional weight method may not offer equal significance to both the Fuel Cost and Emission. The proposed methodology was a normalized objective function with a view of providing equal significance to both the objectives there by obtaining BCS. The solution methodology use the recently suggested Teaching Learning Based Optimization Algorithms (TLBO) and is tested on various test system ranging upto 100 units. The results on six tests system have clearly illustrated that the proposed method is better than weight method. The performance can be improved by combining the algorithms with Classical Legrangian Relaxations Method.

Keywords: Multi Objective Optimization, Teaching Learning Based Optimization, Unit Commitment

Nomenclature

CST_i	Cold startup cost of unit *i* ($)
UC	Unit commitment
TLBO	Teaching learning based optimization
BCS	Best compromised schedule
atlbo	Adaptive TLBO
WM	Weight method
PM	Proposed method
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
NNGC	Normalized net generation cost ($/h)
NNEC	Normalized net emission cost ($/h)
NGC	Net generation cost ($/h)
NEC	Net emission cost ($/h)
$P_{Gi}^{\max}$	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)
$P^{i,t}$	Performance index of *i*-th student at *t*-th iteration
$P^{teacher,t}$	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)

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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) 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[1].

The fossil fuel based power plants emit several contaminants and greenhouse gases that pollute the atmosphere and cause global warming as well. 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. There is thus a need to reduce the pollutants with a view of keeping the air clean and reducing the effects of global warming by including the emissions either in the objective or treating as additional constraints of UC problems[2]. The UC problem thus becomes a multi-objective problem with conflicting objectives since emission minimization conflicts with fuel cost minimization.

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.

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.

The effort in this article encompasses a solution strategy using an adaptive TLBO (ATLBO) with a view of obtaining the Best Compromised Schedule (BCS) for multi-objective UC problem to explore its applicability for emerging power systems. The paper is divided into six sections. Section 1 gives the introduction, section 2 outlines the UC problem, section 3 overviews the TLBO, section 4 suggests an adaptive scheme, section 5 describes proposed method, section 6 discusses the simulation results and section 7 concludes the article.

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

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

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:

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

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,

$$F_i(P_{Gi}^k) = a_i P_{Gi}^{k\,2} + b_i P_{Gi}^k + c_i \tag{7}$$

$$E_i(P_{Gi}^k) = d_i P_{Gi}^{k\,2} + e_i P_{Gi}^k + f_i \tag{8}$$

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:

3.1 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

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

Where,

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

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

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

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

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.

3.2 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:

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

p_p and p_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]

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

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

In multi-objective optimization problems, the objectives are blended by Weight Method (WM) using weight parameter ω., as given in Equation (1). The relative significance given to each of the objectives can be varied by changing the value of ω. When ω is 1, the technique offers the best fuel cost. The fuel cost increases and the emission cost decreases when ω is reduced in steps from 1 to 0. It provides the best emissions when ω equals 0.

In UC problem, the Best Compromised Schedule (BCS) may be defined as the one with equal percent deviations from the optimal solutions corresponding to best generation cost and best emissions besides lying nearer to both of the best solutions[20]. It is to be noted that the generation cost includes both the fuel cost and start-up cost. Setting a ω value of 0.5 in the WM may not yield BCS, as the EED solution methodology does not include the start-up cost. Besides the chosen h parameter does not make the fuel cost and emissions cost components to the same level in the objective function. There is thus a need for a methodology to address the above mentioned drawbacks in obtaining the BCS of the UC problem.

The prime objective of the PM is to make the net-generation cost and net-emission components of the cost function equal to the possible extent over the scheduling period in addition to minimizing the cost function of the UC problem using the ATLBO, while satisfying the systems' equality and inequality constraints. This can be realized by treating ω as a real valued variable in the range of $(0,1)$ in addition to the usual binary UC variables. If ω is treated as a variable, it will directly control the components of fuel cost and emissions, thereby eliminating the h-parameter.

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

Figure 1. Representation of a student.

5.2 Generation of Initial Population

It is difficult to generate feasible solution when initial population is generated at random. All units are almost committed at heavy load while most of them are decommitted at light load. The initial population is therefore generated from the load curve as shown in Figure 2.

5.3 Binary Conversion Mechanism

The binary conversion mechanism, suggested by Kennedy and Eberhart[21] 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.

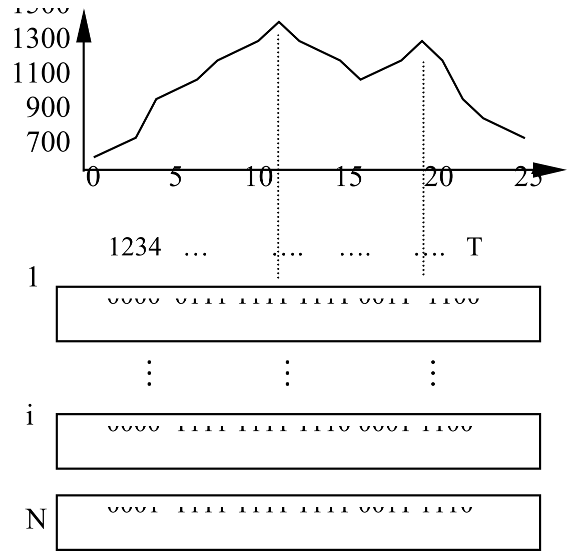

Figure 2. Initial Population.

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

Where,

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

5.4 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.

- If spinning reserve constraint is not satisfied, randomly change an off status unit to on $(0 \rightarrow 1)$.
- If the net minimum power generation of on status units is greater than the power demand, randomly change an on status unit to off $(0 \rightarrow 0)$.
- 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.
- Repeat steps 1-3 till all the constraints are satisfied.

5.5 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[1] 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[22] in order to improve the computational speed.

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

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

The co-ordination equation of the conventional λ–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 Equation (18) for optimal generations,

$$P_{Gi}^k = \frac{\lambda_k - b'_i}{2a'_i} \qquad (19)$$

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,

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

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

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

$$Min \quad \Phi_{F,k}(P_G) = A_k P_D^{k2} + B_k P_D^k + C_k \qquad (23)$$

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_D by P_G in Equation (23)

$$\Phi_{F,k}(P_G) = A_k P_G^{k2} + B_k P_G^k + C_k \qquad (28)$$

Differentiating and equating Equation (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

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

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 Equation(29) and then solve Equation(30) for all generating plants at all intervals
- Stop

5.6 Performance Index Function

The algorithm searches for optimal solution by maximizing a performance index function, which is so tailored that it gives equal significance to both the generation cost and emission components through normalizing the net-generation cost and net-emission components as

$$Maximize \quad PI = \frac{1}{1 + (NNGC + NNEC) + PF * |NNGC - NNEC|} \qquad (31)$$

Where,

NNGC =

$$\left[\frac{\left(\sum_{t=1}^{T} \sum_{i=1}^{N} \left\{ F_i(P_{Gi}^t) + ST_i^t \left(1 - U_{i,t-1}\right) \right\} U_{i,t} \right) - NGC^{\min}}{NGC^{\max} - NGC^{\min}} \right] \times 100 \qquad (32)$$

$$NNEC = \left[\frac{\left(\sum_{t=1}^{T} \sum_{i=1}^{N} E_i(P_{Gi}^t) U_{i,t} \right) - NE^{\min}}{NE^{\max} - NE^{\min}} \right] \times 100 \qquad (33)$$

Equation (31) eliminates the use of h parameter, but requires the values for $NGC^{\min}$, $NGC^{\max}$, $NEC^{\min}$ and $NEC^{\max}$, which can however be obtained through solving UC with EcD and UC with EmD.

5.7 Solution Process

An initial population of students is obtained by generating random values within their respective limits to every individual in the population using the procedure described in section 5.2. The P 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. The flow of the proposed PM for obtaining the BCS of UC problem is shown in Figure 3.

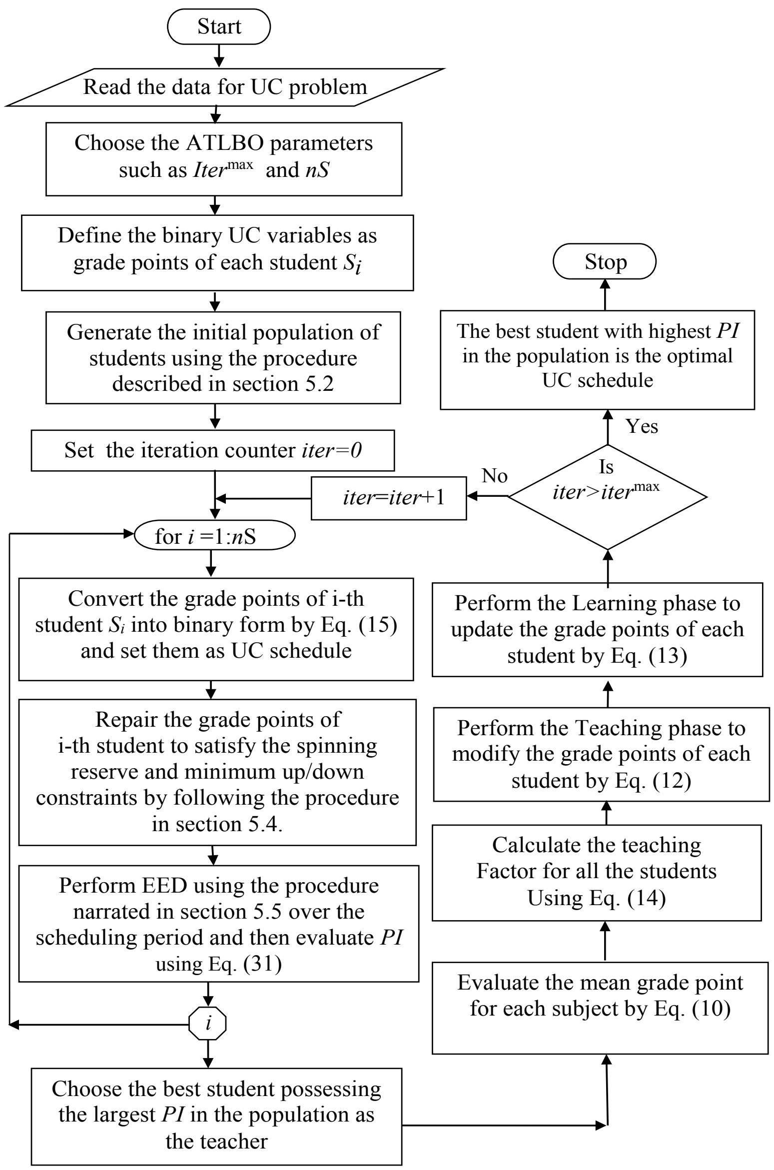

Figure 3. Flow chart of PM.

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[23]. The emission coefficients are taken from[24]. 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 test system, totally 50 trials are performed to study the performance of the PM. The normalized objective function values, *NNGC* and *NNEC* that represent how far the solution is away from the individual best points[20], is used for studying the goodness of the solution. A solution is said to be BCS if the *NNGC* and *NNEC* are in the same range, which can be assessed through calculating the difference between them $DNOV = NNGC - NNEC$. The best and worst values of the individual objectives, required for evaluating the*NNGC*, *NNEC*, *DNOV* and *P* are given for all the test systems in Table 1. The detailed results comprising UC schedule, fuel cost and emissions at each interval, net start-up cost, net generation cost and net emissions of 10-unit system, obtained by PM, are presented in Table 2. The generations of UC schedule over the scheduling period are shown in Figure 4. The net fuel cost, net start-up cost, net generation cost and net emissions for of 10, 20, 40, 60, 80 and 100 unit systems of the PM are given in Table 3. The table also includes the results of WM with a view of comparison.

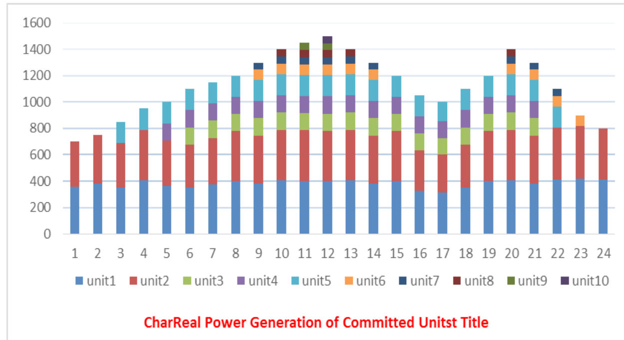

Figure 4. BCS for 10 unit system by PM.

The quality of the BCSs, in terms of *NNGC, NNEC* and *DNOV,* obtained by PM and WM, are pictorially compared in Table 4 for all the test systems. It is obvious that the PM offers *DNOV* of 0.324, which is much lower than that of the WM for 10 unit system, thereby indicating that PM is able to offer BCS. The same can be observed for the remaining test systems. These results clearly indicate that the PM offers the BCS that simultaneously optimizes the generation cost and emissions for all the test systems. The UC schedule along with the optimized weight value (ω) of the PM for 10, 20, 40, 60, 80 and 100 unit systems are given in Table 5.

Table 1. Best and Worst Objective Function Values

Test System	Fuel Cost ($/h)		Emissions (lb/h)	
	Best	Worst	Best	Worst
10-units	563937.687070	601601.784227	32872.500348	44519.972826
20-units	1124587.481774	1198110.751007	65513.164896	89627.171383
40-units	2243372.503499	2392404.201865	130773.588955	177312.704025
60-units	3361567.962523	3581010.286946	195689.171817	265721.535026
80-units	4482079.070863	4774575.495765	260862.040743	352993.674834
100-units	5600754.764095	5975383.453642	326410.540027	442191.145025

Table 2. UC Schedule over scheduling horizon for 10 unit system by PM

		Unit										Fuel Cost $/h	Emissions lb/h
		1	2	3	4	5	6	7	8	9	10		
Interval	1	1	1	0	0	0	0	0	0	0	0	13765.138	855.823
	2	1	1	0	0	0	0	0	0	0	0	14615.868	996.998
	3	1	1	0	0	1	0	0	0	0	0	17306.960	1000.825
	4	1	1	0	0	1	0	0	0	0	0	19008.935	1289.154
	5	1	1	0	1	1	0	0	0	0	0	20507.698	1139.086
	6	1	1	1	1	1	0	0	0	0	0	22889.438	1284.902
	7	1	1	1	1	1	0	0	0	0	0	23739.734	1421.016
	8	1	1	1	1	1	0	0	0	0	0	24591.020	1568.631
	9	1	1	1	1	1	1	1	0	0	0	28159.287	1794.062
	10	1	1	1	1	1	1	1	1	0	0	31046.975	2181.673
	11	1	1	1	1	1	1	1	1	1	0	33124.753	2441.024
	12	1	1	1	1	1	1	1	1	1	1	35219.489	2712.841
	13	1	1	1	1	1	1	1	1	0	0	31046.975	2181.673
	14	1	1	1	1	1	1	1	0	0	0	28159.287	1794.062
	15	1	1	1	1	1	0	0	0	0	0	24591.020	1568.631
	16	1	1	1	1	1	0	0	0	0	0	22019.441	1164.032
	17	1	1	1	1	1	0	0	0	0	0	21114.297	1058.381
	18	1	1	1	1	1	0	0	0	0	0	22889.438	1284.902
	19	1	1	1	1	1	0	0	0	0	0	24591.020	1568.631
	20	1	1	1	1	1	1	1	1	0	0	31046.975	2181.673
	21	1	1	1	1	1	1	1	0	0	0	28159.287	1794.062
	22	1	1	0	0	1	1	1	0	0	0	23459.785	1661.088
	23	1	1	0	0	0	1	0	0	0	0	18004.916	1280.918
	24	1	1	0	0	0	0	0	0	0	0	13765.138	1149.673
Start-Up Cost ($/h)												4090.000	---
Net Fuel Cost ($/h) / Net Emissions (lb/h)												578615.322	37373.760

Table 3. Comparison of Results for BCS of 10 unit system by PM-5

Test System	Method	Fuel cost	Start-up cost	Net cost	Net Emission
10-units	PM	574525.322800	4090.000000	578615.322800	37373.760886
	WM	581818.593321	4540.000000	586358.593321	36242.409549
20-units	PM	1146242.235376	8180.000000	1154422.235376	75382.671833
	WM	1157131.876983	7620.000000	1164751.876983	73465.079738
40-units	PM	2286461.577617	14940.000000	2301401.577617	148892.440978
	WM	2302520.400996	15000.000000	2317520.400996	144228.014578
60-units	PM	3425339.604787	21300.000000	3446639.604787	222666.143067
	WM	3452338.035506	22380.000000	3474718.035506	216086.270295
80-units	PM	4559564.044551	31580.000000	4591144.044551	295645.731979
	WM	4596095.854733	29880.000000	4625975.854733	290110.555829
100-units	PM	5708146.070639	34680.000000	5742826.070639	371208.836981
	WM	5725227.005635	37320.000000	5762547.005635	367393.121495

Table 4. Comparison of Performance Metrics

Test System	Method	NNGC	NNEC	DNOV
10-units	PM	38.970	38.646	0.324
	WM	59.529	28.933	30.596
20-units	PM	40.579	40.929	0.35
	WM	54.628	32.976	21.652
40-units	PM	38.937	38.933	0.004
	WM	49.753	28.910	20.843
60-units	PM	38.767	38.521	0.246
	WM	51.563	29.125	22.438
80-units	PM	37.288	37.754	0.466
	WM	49.196	31.746	17.45
100-units	PM	37.923	38.692	0.769
	WM	43.187	35.397	7.79

Table 5. Weight Parameters by PM

Test System	10-units	20-units	40-units	60-units	80-units	100-units
Weight parameter ω	0.16	0.205	0.195	0.192	0.19	0.205

It is very clear from the above discussions that the performance of the PM is in general superior to that of WM. However, it is to be noted that the PM cannot exactly make the *DNOVs* zero, due to the nonlinear nature of the objectives considered in the UC problem and the unavailability of the solution that makes respective *NNGC* and *NNEC* exactly equal.

7. Conclusions

An elegant algorithm involving ATLBO for obtaining BCS of 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.

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9. References

1. Wood AJ, Wollenberg BF. Power generation, operation and control. John Wiley and sons: New York, 1996.
2. Lamont JW, Obessis EV. Emission dispatch models and algorithms for the 1990's. IEEE Transactions on Power Systems. 1995; 10(2):941–46.
3. Baldwin CJ, Dale KM, Dittrich RF. A study of econmic shutdown of generating units in daily dispatch. AIEE Transactions on PAS. 1960; 78(4):1272–84.
4. Snyder WL, Powell HD Jr, Rayburn JC. Dynamic programming Approach to unit commitment. IEEE Transactions on Power Systems. 1987; PWRS S – 2(2):339–50.
5. Hobbs WJ, Hermon G, Warner S, Sheble GB. An enhanced dynamic programming approach for unit commitment. IEEE Transactions on Power Systems. 1988; 3(3):1201–5.
6. Dillon TS. Integer Programming Approach to the problem of optimal unit commitment with probabilistic reserve Determination. IEEE Transactions on Power Apparatus System. 1978; PAS – 97(6):2154–66.
7. Cohen AI, Yoshimura M. A branch and bound algorithm for unit commitment. IEEE Transactions on Power Apparatus Systems. 1983; PAS – 102(2):444–51.
8. Lee FN. A Fuel – constrained unit commitment method. IEEE Transactions on Power System. 1989; 4(3):691–98.

9. Cheng CP, Liu CW, Liu CC. Unit commitment by Lagrangian Relaxation and genetic algorithm. IEEE Transactions Power Systems. 2000; 15(2):707–14.
10. Yang HT, Yang PC, Huang CL. Evolutionary Programming based economic dispatch for units with no smooth fuel cost functions. IEEE Transactions on Power Systems. 1996; 11(1):112–17.
11. Mantawy AH, Abdel Magid YL, Selim SZ. A Simulated annealing algorithm for unit commitment. IEEE Transactions on Power Systems. 1998; 13(1):197–204.
12. Juste KA, Kita H, Tanaka E, Hasegawa J. An evolutionary programming solution to the unit commitment problem. IEEE Transactions on Power Systems. 1999; 14(4):1452–59.
13. Rao RV, Savsani VJ, Vakharia DP. Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems. Computer Aided Design. 2011; 43(3):303–15.
14. Rao RV, Savsani VJ, Vakharia DP. Teaching-learning-based optimization: A novel optimization method for continuous non-linear large scale problems. Information Sciences. 2012; 183(1):1–15.
15. Rao RV, Patel V. An elitist teaching–learning-based optimization algorithm for solving complex constrained optimization problems. International Journal of Industrial Engineering Computations. 2012; 3(4):535–60.
16. Rao RV, Kalyankar VD. Parameter optimization of modern machining processes using teaching–learning-based optimization algorithm. Engineering Applications of Artificial Intelligence. 2013; 26(1):524–31.
17. Mandal B, Roy PK. Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization. Electrical Power and Energy Systems. 2013; 53(null):123–34.
18. Shabanpour-Haghighi A, Seifi AR, Niknam T. A modified teaching–learning based optimization for multi-objective optimal power flow problem. Energy Conversion and Management. 2014; 77(null):597–607.
19. Rao RV, Patel V. An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems. Scientia Iranica. 2013; 20(3):710–20.
20. Rajasomashekar S, Aravindhababu P. Biogeography-based optimization technique for best compromise solution of economic emission dispatch. Swarm and Evolutionary Computations. 2012; 7(null):47–57.
21. Kennady J, Eberhart RC. A discrete binary version of the particle swarm algorithm, Proceedings of IEEE International Conference on Systems, Man and Cybernetics. Vol 5, Orlando, FL. 1997. p. 4104–8.
22. Palanichamy C, Sundar Babu N. Analytical solution for combined economic and emissions dispatch. Electric Power Systems Research. 2008; 78(7):1129–37.
23. Kazarlis SA, Bakirtzis AG, Petidis V. A genetic algorithm solution to unit commitment problem. IEEE Transactions on Power Systems. 1996; 11(1):83–92.
24. Li Y-F, Pedroni N, Zio E. A memetic evolutionary multi-objective optimization method for environmental power unit commitment. IEEE Transactions on Power Systems. 2013; 28(3):2660–69.