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 Lagrangian Relaxations Method.

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

Nomenclature

| Symbol | Description |
|--------|-------------|
| CST<sub>i</sub> | Cold startup cost of unit <i>i</i> ($/h) |
| UC     | Unit commitment |
| TLBO   | Teaching learning based optimization |
| BCS    | Best compromised schedule |
| atlbo  | Adaptive TLBO |
| WM     | Weight method |
| PM     | Proposed method |
| a, b, c | Fuel cost coefficients |
| d, e, f | Emission coefficients |
| <i>E</i><sub>k</sub>(<i>P</i><sub>Gi</sub>) | Emission function (lb/h) |
| <i>F</i><sub>i</sub>(<i>P</i><sub>Gi</sub>) | Generator fuel cost function ($/h) |
| <i>Φ</i><sub>fk</sub>(<i>P</i><sub>Gi</sub>,<i>U</i>) | Objective function to be minimized over the scheduling period |
| HST<sub>i</sub> | Hot startup cost of unit <i>i</i> ($) |
| iter<sup>max</sup> | Maximum number of iterations |
| N      | Total number of generating units |
| NNGC   | Normalized net generation cost ($/h) |
| NEC    | Net emission cost ($/h) |
| <i>P</i><sub>Gi</sub><sup>max</sup> | Maximum real power generation of unit <i>i</i> (MW) |
| <i>P</i><sub>Gi</sub><sup>min</sup> | Minimum real power generation of unit <i>i</i> (MW) |
| <i>P</i><i>'</i><sub>i</sub> | Generation output power of unit <i>i</i> at <i>k</i>-th interval (MW) |
| <i>P</i><sub>D</sub><sup>k</sup> | Load demand at <i>k</i>-th interval (MW) |
| <i>p</i><i>teacher</i><i>t</i> | Performance index of the teacher at <i>t</i>-th iteration |
| <i>p</i><i>i</i><i>t</i> | Performance index of <i>i</i>-th student at <i>t</i>-th iteration |
| <i>R</i><i>k</i> | Spinning reserve at <i>k</i>-th interval (MW) |
| rand   | A random number generated in the range [0,1] |
| <i>ST</i><sub>i</sub><sup>k</sup> | Startup cost of unit <i>i</i> at <i>k</i>-th interval ($) |
| <i>T</i> | Total number of hours |
| <i>T</i><sup>cold</sup><sub>i</sub> | Cold start hour of unit <i>i</i> (hours) |

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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.

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. 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, 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, optimal reactive power flow and optimal power flow 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

subject to,

Power balance constraint

Spinning reserve constraint:

Generation limit constraints:

Minimum up and down time constraints:

Start-up Cost:

where

and
Where,

\[ F(P_{Gi}^k) = a_i P_{Gi}^{k+2} + b_i P_{Gi}^k + c_i \]  (7)

\[ E(P_{Gi}^k) = d_i P_{Gi}^{k+2} + e_i P_{Gi}^k + f_i \]  (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

\[ \Delta S_{j}^{t} = \text{rand}(0,1) \times (S_{j,\text{ave}}^{t} - t_{j} S_{j}^{t,\text{ave}}) \]  (9)

Where,

- \( S_{j,\text{ave}}^{t} \) is the mean grade of the j-th subject at t-th iteration and computed by
  \[ S_{j,\text{ave}}^{t} = \frac{1}{n} \sum_{i=1}^{n} S_{j}^{t} \]  (10)
- \( S_{j}^{t,\text{ave}} \) is the grade point of the j-th subject of the teacher at t-th iteration and computed by
  \[ S_{j}^{t,\text{ave}} = \frac{1}{n} \sum_{i=1}^{n} S_{j}^{t} \]  (10)
- \( S_{j}^{t} \) is the grade point of the j-th subject of the i-th student,
- \( t_{j} \) is the teaching factor, which decides the value of mean to be changed and can be either 1 or 2, evaluated by
  \[ t_{j} = \text{round}([1 + \text{rand}(0,1)][1,2]) \]  (11)

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

\[ S_{j}^{t+1} = S_{j}^{t} + \Delta S_{j}^{t} \]  (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:

\[
S_{j}^{t+1} = \begin{cases} 
S_{j}^{t} + \text{rand} \times (S_{j}^{t} - S_{j}^{t}) & \text{if } P_{i} > P_{q} \\
S_{j}^{t} + \text{rand} \times (S_{j}^{t} - S_{j}^{t}) & \text{if } P_{i} < P_{q} 
\end{cases}
\]  (13)

\( p \) and \( q \) 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

\[
t_{j}^{t} = \begin{cases} 
\frac{P_{i}^{t,\text{ave}}}{P_{i,\text{teacher}}^{t,\text{ave}}} & \text{if } P_{i,\text{teacher}}^{t,\text{ave}} \neq 0 \\
1 & \text{otherwise}
\end{cases}
\]  (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 \( \omega \), as given in Equation (1). The relative significance given to each of the objectives can be varied by changing the value of \( \omega \). When \( \omega \) is 1, the technique offers the best fuel cost. The fuel cost increases and the emission cost decreases when \( \omega \) is reduced in steps from 1 to 0. It provides the best emissions when \( \omega \) 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. It is to be noted that the generation cost includes both the fuel cost and start-up cost. Setting a \( \omega \) 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 $\omega$ as a real valued variable in the range of $(0,1)$ in addition to the usual binary UC variables. If $\omega$ 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, $U_{i,k}$ which represents on/off status of $i$-th unit at $k$-th interval in matrix form as shown in Figure 1.

$$
S = \begin{bmatrix}
1 & U_{1,1} & U_{1,2} & \ldots & U_{1,t} \\
2 & U_{2,1} & U_{2,2} & \ldots & U_{2,T} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
N & U_{N,1} & U_{N,2} & \ldots & U_{N,T} \\
\end{bmatrix}
$$

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\textsuperscript{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.

$$
S_p^{i+1} = \begin{cases} 
1 & \text{if } B^T < G(S_p^{i+1}) \\
0 & \text{otherwise} 
\end{cases} 
$$

Where,

$$
G(S_p^{i+1}) = \frac{1}{1 + \exp(-S_p^{i+1})} 
$$

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 $\lambda$ 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\(^2\) in order to improve the computational speed.

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

\[
a_i' = \omega a_i + (1-\omega)hd_i \\
b_i' = \omega b_i + (1-\omega)he_i \\
c_i' = \omega c_i + (1-\omega)hf_i
\]

(17)

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

\[
G_i = \frac{\lambda_k - b_i'}{2a_i'} \\
P_{Gi}^k = \frac{\lambda_k - b_i'}{2a_i'}
\]

(18)

Rearranging Equation (18) for optimal generations,

\[
G_i = \frac{\lambda_k - b_i'}{2a_i'} \\
P_{Gi}^k = \frac{\lambda_k - b_i'}{2a_i'}
\]

(19)

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

\[
P_{Gi}^k = \frac{P_D^k - \rho - b_i' \sigma}{2a_i' \sigma}
\]

(20)

Where,

\[
\rho = \sum_{i=1}^{N} \frac{b_i'}{2a_i'}
\]

(21)

\[
\sigma = \sum_{i=1}^{N} \frac{1}{2a_i'}
\]

(22)

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

\[
Min \quad \Phi_{F,k}(P_G) = A_kP_G^{i,k} + B_kP_G^k + C_k
\]

(23)

Where,

\[
A = \sum_{i=1}^{N} \frac{1}{4a_i' \sigma^2}
\]

(24)

\[
B = \sum_{i=1}^{N} \frac{\rho}{2a_i' \sigma^2}
\]

(25)

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

\[
P_{Gi}^k = \frac{\lambda_k - b_i'}{2a_i'}
\]

(30)

The algorithm is obtained below:

- Read the system data
- Calculate the cost coefficients $a_i', b_i'$ and $c_i'$
- Evaluate the constants $\rho, \sigma, A, B$ and $C$
- Evaluate $\lambda^o$ 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

\[
Maximize \quad PI = \frac{1}{1+(NNGC + NNEC) + PF \times [NNGC - NNEC]} \quad (31)
\]

Where,

\[
NNGC = \left[ \sum_{i=1}^{N} \sum_{j=1}^{N} F_i(P_{Gi}^j) + ST_i (1-U_{ij-1})U_{ij} \right] \times 100 \quad (32)
\]

\[
NNGC_{max} - NNGC_{min}
\]
\[
NNEC = \left( \sum_{i=1}^{N} \sum_{r=1}^{T} E_{i,r} \left(P_{G_i}^{r} U_{i,t} \right) - NE_{\min} \right) \times 100
\] (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.

![Flow chart of PM.](image-url)
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 in23. The emission coefficients are taken from24. 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 points20, 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 (\( \omega \)) 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    | 112487.481774  | 1198110.750007  | 65513.164896   | 89627.171383    |
| 40-units    | 224372.503499  | 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

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

| Start-Up Cost ($/h) | 4090.000 |
|--------------------|----------|
| Net Fuel Cost ($/h) | 578615.322 |
| / Net Emissions (lb/h) | 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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