Unit Commitment with Ancillary Services in a Day-Ahead Power Market

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Abstract: This paper integrates Discrete Particle Swarm Optimization (DPSO) and Sequential Quadratic Programming (SQP) to propose a DPSO-SQP method for solving unit commitment problems for ancillary services. Through analysis of ancillary services, including Automatic Generation Control (AGC), Real Spinning Reserve (RSR), and Supplemental Reserve (SR), the cost model of unit commitment was developed. With the requirements of energy balance, ancillary services, and operating constraints considered, DPSO-PSO was used to calculate the energy supply of each source, including the associated AGC, RSR, and SR, and the operating cost of a day-ahead power market was calculated. A study case using the real data from thermal units of Taipower Company (TPC) and Independent Power Producers (IPPs) demonstrated effective results for the “summer” and “non-summer” seasons, as classified by TPC for the two charging rates. According to the test cases in this research, costs without ancillary services in non-summer and summer seasons are higher than those with ancillary services. The simulation results are also compared with the Genetic Algorithm (GA), Evolutionary Programming (EP), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). DPSO-PSO shows effectiveness in solving unit commitment problems with enhanced sorting efficiency, and a higher probability of reaching the global optimum.

Keywords: Particle Swarm Optimization; Sequential Quadratic Programming; ancillary services; unit commitment

1. Introduction

Nuclear plants and large-scale thermal plants generally supply base loads, while medium thermal plants and water plants supply medium loads, and the peak load is supplied by gas turbines and diesel engines. The major purpose of unit commitment is to determine how to commit various units to satisfy the 24 h load demands under related constraints [1]. Ancillary services have now become indispensable in terms of operation [2,3]. If ancillary services are absent, there may be a series of problems related to safety, reliability, and power quality. Unit commitment with ancillary services is a more complicated issue than the traditional unit commitment problem, as unit commitment with ancillary services is a combinatorial, mixed-integer, continuous and multi-dimensional problem of “energy” and “capacity”. In the power transaction market, the load forecast of energy supply and the ancillary service capacity need to be simultaneously evaluated. However, unit commitment in ancillary services must consider the fact that online units can rapidly adjust to satisfy the ancillary services’ capacity to safely conform to the operational standards of a power system. As there are more variables and more confined constraints, optimal power dispatch becomes very tedious and difficult to achieve.

By considering the operations of various plants, they can rapidly respond to the load change with all units coordinating for energy balance. The appropriate supply of ancillary services requires the establishment of economic models that can pay for these services,
whereby special attention is given to Automatic Generation Control (AGC), Real-time Spinning Reserve (RSR), and Supplemental Reserve (SR) in TPC [4]. AGC, including up-regulation and downregulation, is the first level of regulation in reserve for the system operator. RSRs are units that can respond quickly to accidents or load increases. SR plays an important role in maintaining system security, as this reserve is more time-consuming, and is used when RSR cannot satisfy the reserve needs. Ancillary services, as required to ease the previously scheduled generating capacity, are based on online generating plants. Therefore, the operations of the energy market should consider ancillary services in unit commitment schedules.

Unit commitment for the power market is an urgent problem for the TPC. The scheduling strategy contains a sequential schedule that determines the unit on/off state in each time interval, and assigns the power scheduling and ancillary services’ scheduling results. There are many constraints for unit commitment in the power market, such as unit generation limits, on/off states, operating time, and ramping rates. Many local minima could be expected with mixed integers, which increase the complexity of the problem. It is difficult to find the optimal solution using a traditional mathematical tool. Ref. [5] concluded that unit commitment, as addressed before 2003, may face problems of dimensionality, excessive computational time, and local optimality. Recently, artificial intelligence algorithms are being used in unit commitment optimization [6–10]; while part of the artificial intelligence algorithms can overcome various constraints, convergent rates are poor if there are numerous variables, and a long solving time can be expected. Among references regarding ancillary services, [11] used mixed-integer programming and an artificial neural network to analyze and simulate the condition of a power market in order to solve the competitive bidding strategy of ancillary services. Ref. [12] discussed the ancillary services of different reserve unit capacities, and combined the settlement price with an optimum allocation in order to properly implement the strategy of demand response in the system. Ref. [13] proposed a payment mechanism, and properly implemented energy costs and demand charges by considering energy dispatch in ancillary services. Ref. [14] used dynamic optimum power flow to analyze the dispatch of energy in relation to ancillary services. In terms of safety and unit commitment emergency analysis, [15] used N-k fault analysis to seek the work of the demand response in ancillary services, in order to address disasters caused by emergencies. Since microgrids have more flexibility in coordinating power sources and loads, they are usually [16] considered as a candidate for the provision of ancillary services. Ref. [17] used a renewable ancillary service to enhance power system operations. Regarding the ancillary services of frequency control, voltage regulation, and active power management, the allocation and management of costs are the most important issues of system operation [18–21]. Ref. [22] used pumped storage hydropower plants to provide the ancillary services for balancing supply and demand. The AGC unit’s quantitative evaluation, unit selection [23], and power transmission line in ancillary service cost allocation [24] are all discussed. Real-time ancillary service is now a non-negligible function in an electrical deregulated environment.

This paper proposes a hybrid DPSO-SQP by combining Discrete Particle Swarm Optimization (DPSO) [25] with Sequential Quadratic Programming (SQP) [26] to compute the power scheduling of various units and ancillary services in the power market. PSO is introduced with simplicity, easy implementation, and mutual independence in simulation, whereby the particles only need to exchange information once with the group optimum. However, the performance of the PSO is related to the initial distribution of the swarm, meaning that if the initial states of the swarm are near the local optimum region, the swarm may become trapped, which is the disadvantage of PSO. Unit commitment in ancillary services can be considered as two sub problems: “determining the on/off state of units in various time intervals” and “electricity generation assignment”, which has many constraints. Generally speaking, while appropriate PSO parameter settings can accelerate the convergence, a good set of parameters may not be easy to come by. It is generally obtained from many experiences or from other settings with sophis-
ticated enumeration process, thus, the problem is further complicated. This paper uses DPSO to compute the discrete mode of the “on/off state of units” for various time intervals, where parameter settings can be effectively reduced. SQP will then calculate power generation and ancillary services. The proposed DPSO-SQP used the thermal units of TPC and Independent Power Producers (IPPs) as the test sample, and the simulation results are compared with other algorithms, including the Genetic Algorithm (GA), Evolutionary Programming (EP), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) [27–30]. The accuracy and robustness of the algorithm also show a higher probability of reaching a global optimum.

2. Problem Formulation

The unit commitment with ancillary services should satisfy the load demand, and must consider if the online units can respond to the load change in a short time period, i.e., the demands from AGC, RSR, and SR. The mathematical model involves multiple variables, which are mostly confined to the constraints of unit characteristics. This paper aims to minimize the total cost, including electric energy, AGC, RSR, and SR costs. That is,

\[
\text{Min.} C_T = \text{electric energy cost} + \text{AGC cost} + \text{RSR cost} + \text{SR cost}
\]

\[
C_T = \frac{h}{\sum_{t=1}^{h} \left[ \sum_{i=1}^{m} \left( F_i \left( P_i^t \right) U_i^t \right) + \left( ST_i^t U_i^t \left( 1 - U_i^{t-1} \right) \right) + \sum_{i=1}^{m} \left( F_{AGC,i} \left( P_{AGC,i}^t \right) U_i^t \right) \right]}
\]

(1)

The startup cost is divided into hot-start and cold-start cost, as expressed by

\[
ST_i^t = \begin{cases} 
\text{hotstartcost} & \text{when } T_{i}^{\text{off}} \leq U_{i}^{\text{off}} \leq H_{i}^{\text{off}} \\
\text{coldstartcost} & \text{when } U_{i}^{\text{off}} > H_{i}^{\text{off}} 
\end{cases}
\]

(2)

Other related constraints are [4,5]

a. Load balance

\[
\sum_{i=1}^{m} P_i^t \times U_i^t = D_t
\]

(3)

b. Upper and lower limits of unit generation

\[
P_{i,\text{min}} \leq P_i^t \leq P_{i,\text{max}} \quad I = 1, \ldots, m
\]

(4)

c. Ramping down/up rate limitations

\[
P_i^{t-1} - RD_i \leq P_i^t \leq P_i^{t-1} + RU_i \quad I = 1, \ldots, m
\]

(5)

d. Minimum up/down time

\[
U_i^t = 1 \text{ for } \sum_{t=t_1,\text{on}}^{t_2,\text{on}} U_i^t \geq \text{MUT}_i
\]

(6)

\[
U_i^t = 0 \text{ for } \sum_{t=t_1,\text{off}}^{t_2,\text{off}} U_i^t \geq \text{MDT}_i
\]

(7)

The AGC rate for the load up/down is 3 min, RSR has a load up rate of 30 min, and SR has a load up rate of 60 min. Related constraints are described as follows [5]:
A. AGC limitation
   a. The AGC demand is expressed as
   \[ \sum_{i=1}^{m} P_{AGC,j}^{t,k=3} = D_{AGC,j}^{k=3} \] (8)
   b. The response to the rise/down rate of 3 min can be expressed as
   \[ p_{AGC,j}^{t,k=3} - P_{AGC,j}^{t,k=3} \leq UR_{AGC,j}^{k=3} \] (9)
   \[ p_{AGC,j}^{t,k=3} - P_{AGC,j}^{t,k=3} \leq DR_{AGC,j}^{k=3} \] (10)

B. RSR limitation
   a. The RSR demand is expressed as
   \[ \sum_{i=1}^{m} P_{RSR,j}^{t,k=30} = D_{RSR,j}^{k=30} \] (11)
   b. The rise rate of 30 min is expressed as
   \[ p_{RSR,j}^{t,k=30} - P_{RSR,j}^{t,k=30} \leq UR_{RSR,j}^{k=30} \] (12)

C. SR limitation
   a. The SR demand is expressed as
   \[ \sum_{i=1}^{m} P_{SR,j}^{t,k=60} = D_{SR,j}^{k=60} \] (13)
   b. The rise rate of 60 min is expressed as
   \[ p_{SR,j}^{t,k=60} - P_{SR,j}^{t,k=60} \leq UR_{SR,j}^{k=60} \] (14)

3. Proposed Methodology

   Regarding the unit commitment problem, two types of variables must be computed:
   (1) unit state—\( U_i(t) \) is an integer variable;
   (2) generation output—\( P_i(t) \) is a continuous variable.

   The proposed DPSO-SQP uses DPSO to compute the unit state in the state matrix,
   and uses SQP to compute the assigned generation output of various units. The proposed
   methodology is described below.

3.1. DPSO

   The traditional PSO is modified with simplicity, easy implementation, and mutual
   independence, where the particles only exchange information once with the group optimum.
   In the traditional PSO, the position and the velocity of general particles can be
   expressed as [29]
   \[ X_{i,d} = (x_{i,1}, x_{i,2}, \ldots, x_{i,D}) \] (15)
   \[ V_{i,d} = (V_{i,1}, V_{i,2}, \ldots, V_{i,D}) \] (16)

   The self-cognition model can be expressed as
   \[ V_{i,d}^{j+1} = V_{i,d}^{j} + c_1r_1(X_{best,i}^{j} - X_{i,d}^{j}) \] (17)
and the social model can be expressed as

\[ V_{jd}^{i+1} = V_{jd}^i + c_2 r_2 (Gbest_j^i - X_{jd}^i) \]  

(18)

The two behavior patterns can be integrated, and the updating of the PSO is expressed as

\[ V_{jd}^{i+1} = V_{jd}^i + c_1 r_1 (X_{best}^i_j - X_{jd}^i) + c_2 r_2 (Gbest_j^i - X_{jd}^i) \]  

(19)

\[ X_{jd}^{i+1} = X_{jd}^i + V_{jd}^{i+1} \]  

(20)

Parameters \( c_1 \) and \( c_2 \) have a significant effect on the search result, but it is difficult to get the appropriate parameters. Since good parameters are difficult to come by, PSO is modified and improved in this paper, where parameter settings can be effectively reduced for the discrete mode by using the following formula:

\[ V_{jd}^{i+1} = V_{jd}^i + \text{round}(r_1) \ast (X_{best}^i_j - X_{jd}^i) + \text{round}(r_2) \ast (Gbest_j^i - X_{jd}^i) \]  

(21)

where \( \text{round} \) is the discriminant of rounding for simplifying the equation, which limits the output solution to binary states of 0 and 1. Since \( c_1 \) and \( c_2 \) are replaced, the computing process of DPSO will be relatively stable with binary values.

3.2 SQP

SQP is derived from Lagrangian relaxation. The idea is to convert the problem into a dual-optimization problem, where the problem and its numerous constraints are simplified. With the unit on/off state obtained from DPSO and the assigned generation output calculated by SQP, the minimum total production cost can be calculated. The cost function of units is described with a polynomial function, expressed as [26]

\[ \text{Minimize } f(x) = \frac{1}{2} x^T H x + b^T x + c \]  

subject to:

- \( g_i(x) = 0 \) \( i = 1, 2, \ldots, m \)
- \( g_i(x) \leq 0, i = m + 1, m + 2, \ldots, n \)
- \( x_l \leq x \leq x_u \)

where \( H \) is the Hessian Matrix, \( g_i(x) \) is the equal/inequality function, \( x_l/x_u \) is the lower/upper limit of the variable \( x \).

The SQP solving process contains three steps.

a. Update the Hessian matrix

\[ H_{k+1} = H_k + \frac{q_k q_k^T}{q_k^T s_k} - \frac{H_k^T H_k}{s_k^T H_k s_k} \]

where

\[ s_k = x_{k+1} - x_k \]

\[ q_k = \nabla f(x_{k+1}) + \sum_{i=1}^{m} \lambda_i \nabla g_i(x)_{k+1} - (\nabla f(x_k) + \sum_{i=1}^{m} \lambda_i \nabla g_i(x)_k) \]  

(23)

b. Compute quadratic programming, as expressed in Equation (22).

c. Use Line Search and the Merit Function to update system parameters.

\[ \text{Line Search: } x_{k+1} = x_k + s_k d_k \]  

(24)
Merit Function:

\[ \Phi(x) = f(x) + \sum_{i=1}^{m} r_i g_i(x) + \sum_{i=1}^{m} r_i \max \{0, g_i(x)\} \]

(25)

3.3. DPSO-SQP Implementation Procedure

The procedure of using DPSO-SQP to compute unit commitment with ancillary services is described as follows.

1. Input the load demand, as well as the AGC, RSR, and SR demands on ancillary services.
2. Input the operating limits of the units in ancillary services and the costs of electric energy, AGC, RSR, and SR.
3. Set the maximum population size \( j_{\text{max}} \) and maximum number of iterations \( t_{\text{max}} \) of DPSO.
4. Import the equality and inequality constraints into the SQP program.
5. Initialize the search area, and set the initial position with a local random search.
6. Copy the initial position to the generated optimum particle position.
7. Use DPSO to solve the states of units in a state matrix.
8. Use SQP to compute the generation output of various units, and calculate the total cost.
9. Update the optimal solutions of \( X_{\text{best}}^j \) and \( G_{\text{best}}^j \).
10. Go to (7) for the next generation.
11. If the preset maximum number of iterations is reached, iteration terminates, otherwise go to (5).
12. Export the minimum cost and the assigned generation output of various units, including electric energy, AGC, RSR, and SR.

The flow chart of the DPSO-SQP problem is shown in Figure 1.

Figure 1. Flow chart of DPSO-SQP applied to unit commitment with ancillary services.
4. Simulation Results

Many study cases were conducted for the thermal units of TPC and IPP, including 14 coal-fired units, 23 gas-fired units, and 6 oil-fired units of TPC, and 5 coal-fired units and 9 gas-fired units of IPP. There are 57 units in total. The maximum generation output, minimum generation output, ramping rates, electric energy price, and startup costs are shown in [31]. The minimum operating time of a coal-fired unit is set as 8 h, the minimum operating time of a gas-fired unit is set as 4 h, and the minimum operating time of an oil-fired unit is set as 6 h. A typical day shown as an example is chosen from the middle ten days of March, and another single day example is taken from the first ten days of July in Taiwan in 2016. The single-day load demands represent the summer and non-summer seasons as shown in Figures 2 and 3. The daily load demand is from 1.2 MW to 2.35 MW for non-summer and from 1.9 MW to 2.6 MW for summer. The demand of AGC is assumed to be 2% of the load demand, the RSR is 3%, and the SR is 5% of the load.

![Figure 2. Load demand in non-summer.](image1)

![Figure 3. Load demand in summer.](image2)

4.1. Unit Commitment with Ancillary Services during Non-Summer

With 57 generator units, four costs per unit including energy, AGC, RSR, and SR, were used. Similarly, four assigned quantities per unit were used. Figure 4 shows the results calculated by DPSO-SQP. The total demands for the electric energy, AGC, RSR, and SR are 493,526 MWh, 9845 MWh, 14,790 MWh, and 24,663 MWh, respectively. The daily cost of unit commitment for the non-summer day is MNT 918.020 (NTD million, USD 1 = NTD 28).
The electric energy and the demands on ancillary services for non-summer are shown in Tables 1 and 2. The coal-fired unit of TPC and IPP provided 52.02% of the electric energy, while the gas-fired unit of TPC and IPP provided 47.32%. The most ancillary services are provided by gas units: AGC (98.58%), RSR (100.00%), and SR (99.83%). The oil-fired unit has a higher cost and provides much less electric energy and ancillary services.

**Figure 4.** Unit commitment in non-summer.

### Table 1. Assigned quantities of various units on a typical non-summer day.

| Type of Unit | Electric Energy (MWh) | AGC Demand (MWh) | RSR Demand (MWh) | SR Demand (MWh) |
|--------------|-----------------------|------------------|------------------|-----------------|
| **TPC**      |                       |                  |                  |                 |
| Coal-fired unit | 182,400               | 0                | 0                | 0               |
| Gas-fired unit | 204,157               | 5710             | 4943             | 7803            |
| Oil-fired unit | 3240                  | 140              | 0                | 70              |
| **IPP**      |                       |                  |                  |                 |
| Coal-fired unit | 74,348                | 0                | 0                | 0               |
| Gas-fired unit | 29,381                | 3995             | 9847             | 16,818          |
| **Total**    | 493,526               | 9845             | 14,790           | 24,663          |

### Table 2. Proportions of various units on a typical non-summer day.

| Type of Unit | Electric Energy (%) | AGC Demand (%) | RSR Demand (%) | SR Demand (%) |
|--------------|---------------------|----------------|----------------|---------------|
| **TPC**      |                     |                |                |               |
| Coal-fired unit | 36.96%              | 0.00%          | 0.00%          | 0.00%         |
| Gas-fired unit | 41.37%              | 58.00%         | 33.42%         | 31.64%        |
| Oil-fired unit | 0.66%               | 1.42%          | 0.00%          | 0.17%         |
| **IPP**      |                     |                |                |               |
| Coal-fired unit | 15.06%              | 0.00%          | 0.00%          | 0.00%         |
| Gas-fired unit | 5.95%               | 40.58%         | 66.58%         | 68.19%        |
| **Total**    | 100.00%             | 100.00%        | 100.00%        | 100.00%       |

### 4.2. Unit Commitment in Summer

A typical summer day solved by DPSO-SQP is shown in Figure 5. The total demands for the electric energy, AGC, RSR, and SR are 55,3734 MWh, 11,041 MWh, 16,605 MWh, and 27,681 MWh, respectively. The daily cost of the unit commitment on this summer day is MNT 1094.307.

The electric energy and demands on ancillary services on a typical summer day are shown in Tables 3 and 4. The gas-fired units of TPC and IPP provided 51.48% energy. The gas-fired units also provided most ancillary services: AGC (86.78%), RSR (89.02%), SR 46.28%. The electric energy of an oil-fired unit in the summer day is higher than that in the non-summer season by 8655 MWh (i.e., 2.15%) and the proportions of AGC (13.21%), RSR (10.98%), and SR (53.72%) also greatly increased.
Figure 5. Unit commitment in summer.

Table 3. Assigned quantities of various units on a typical summer day.

| Type of Unit | Electric Energy (MWh) | AGC Demand (MWh) | RSR Demand (MWh) | SR Demand (MWh) |
|--------------|-----------------------|------------------|------------------|-----------------|
| TPC          |                       |                  |                  |                 |
| Coal-fired unit | 182,400             | 0                | 0                | 0               |
| Gas-fired unit | 231,638              | 3147             | 4231             | 6580            |
| Oil-fired unit | 11,895               | 1459             | 1823             | 14,869          |
| IPP          |                       |                  |                  |                 |
| Coal-fired unit | 74,350              | 0                | 0                | 0               |
| Gas-fired unit | 53,451               | 6435             | 10,551           | 6232            |
| Total        | 553,734              | 11,041           | 16,605           | 27,681          |

Table 4. Proportions of various units on a typical summer day.

| Type of Unit | Electric Energy | AGC Demand | RSR Demand | SR Demand |
|--------------|-----------------|------------|------------|-----------|
| TPC          |                 |            |            |           |
| Coal-fired unit | 32.94%        | 0.00%      | 0.00%      | 0.00%     |
| Gas-fired unit | 41.83%        | 28.50%     | 25.48%     | 23.77%    |
| Oil-fired unit | 2.15%         | 13.21%     | 10.98%     | 53.72%    |
| IPP          |                 |            |            |           |
| Coal-fired unit | 13.43%        | 0.00%      | 0.00%      | 0.00%     |
| Gas-fired unit | 9.65%         | 58.28%     | 63.54%     | 22.51%    |
| Total        | 100.00%        | 100.00%    | 100.00%    | 100.00%   |

This paper uses DPSO-SQP to calculate the minimum cost of electric energy in summer and non-summer, which are MNT 918.020 and MNT 900.081, respectively. According to the case study in this paper, costs in non-summer and summer are higher without ancillary services by MNT 17.939 and MNT 36.857, as shown in Table 5. The cost saving of unit commitment with ancillary services in summer is twice as high as that in non-summer. As power system operations are often accompanied by uncertainties—especially nowadays by the impact of renewable energies, where the generation could have a sudden change due to volatile weather conditions—appropriate ancillary service is important to ensure the safe and stable operation of the system, which must be considered in the power market.

Table 5. Electric energy and ancillary service cost comparison.

|                      | Non-Summer | Summer   |
|----------------------|------------|----------|
| Unit commitment with ancillary service | MNT 918.020 | MNT 1094.307 |
| Unit commitment without ancillary service | MNT 900.081 | MNT 1057.450 |
| Gap                  | MNT 17.939 | MNT 36.857 |
4.3. Convergent Characteristic Analysis

The convergent characteristic of DSPO-SQP analysis is shown in Figure 6. The PSO, SA, GA, and EP are all compared. According to Figure 6, DPSO-SQP can reach convergence for about 65 iterations, and has a better convergent rate than other evolutionary algorithms. Table 6 shows the best values achieved by various algorithms. It shows that DPSO-SQP has the capability of reaching the global optimum better than other algorithms.

Table 6. Comparison of the best values of different algorithms.

|                  | Summer (NTD)   | Non-Summer (NTD) |
|------------------|----------------|------------------|
| DPSO-SQP         | 1,094,306.618  | 918,019.664      |
| PSO              | 1,097,463.111  | 925,090.938      |
| GA               | 1,098,729.402  | 931,661.242      |
| EP               | 1,098,374.348  | 932,800.777      |
| SA               | 1,100,455.785  | 933,989.690      |

Table 7 shows the robustness of DPSO-SQP. It can be shown that DPSO-SQP is more robust and reaches the optimum level more often than other evolutionary algorithms,
where the minimums may vary and often trapped in a local optimum. The number of trials reaching the optimum level (NRO) shows that DPSO-SQP is very robust.

Table 7. The performance tests of various methods.

| Method | DPSO-SQP | PSO | SA | GA | EP |
|--------|----------|-----|----|----|----|
| Item   | AET      | NRO | AET| NRO| AET| NRO |
| Summer | 0.3104   | 36  | 0.3268 | 32  | 0.1828 | 4  | 0.5083 | 2  | 0.5094 | 10 |
| Non-summer | 4.6384 | 28  | 5.7441 | 24  | 10.956 | 6  | 11.1013 | 5  | 8.6657 | 6  |

AET: average execution time (sec.); NRO: number of trials reaching the minimum.

5. Conclusions

Ancillary services are of crucial importance to power supply safety and reliability in the power market. The power scheduling must evaluate the demand on ancillary services, and procure sufficient ancillary services to meet that demand. For generator scheduling, the optimum unit commitment needs to consider ancillary services in terms of reducing costs. Our case study with real data from TPC and IPPs shows an efficient algorithm for power dispatch in a market environment with ancillary services. According to the case study, costs in non-summer and summer are higher by MNT 17.939 and MNT 36.857 without ancillary services. The cost savings of unit commitment with ancillary services in summer are twice as high as those in non-summer seasons. By considering the uncertainties of the new energy from renewables alongside the traditional load change, appropriate ancillary services are important to ensure a stable and safe power network that reduces operating risks.

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Nomenclature

Acronyms
AGC Automatic Generation Control
DPSO Discrete Particle Swarm Optimization
EP Evolutionary Programming
GA Genetic Algorithm
IPPs Independent Power Producers
PSO Particle Swarm Optimization
RSR Real Spinning Reserve
SQP Sequential Quadratic Programming
SR Supplemental Reserve
SA Simulated Anneal
TPC Taipower Company
Constraints

\[ D_{AGC}^{k=3} \] AGC demand in the \( t \)

\[ D_{RGR}^{k=3,j} \] Demand reduction value of the \( i \)-th unit within 3 min

\[ D_{AGR}^{k=30} \] RSR demand in the \( t \)-th time interval

\[ D_{SR}^{k=60} \] SR demand in the \( t \)-th time interval

\[ M_{UJ} \] Minimum up time of the \( i \)-th unit

\[ M_{DJ} \] Minimum down time of the \( i \)-th unit

\[ P_{F_{\max}}^{i} / P_{F_{\min}}^{i} \] Maximum/minimum power generation limitations of the \( i \)-th unit

\[ P_{x_{\max}}^{i} \] AGC operation of \( i \)-th unit participating in the \( t \)-th time interval

\[ P_{x_{\max}}^{i} \] RSR operation of \( i \)-th unit participating in the \( t \)-th time interval

\[ P_{x_{\max}}^{i} \] SR operation of \( i \)-th unit participating in the \( t \)-th time interval

\[ RU_{i} / RD_{i} \] Ramp up/down rate limitations of unit \( i \)

\[ t_{u_{\up}} / t_{u_{\down}} \] Start and stop time intervals of the continuous shutdown of the unit

Variables

\[ d \] Each particle has a \( d \) dimension

\[ c_{1} \] Moving parameter of individual particle value updating

\[ c_{2} \] Moving parameter of the particle following the overall value

\[ P_{i}^{j} \] The fuel cost of unit \( i \)

\[ F_{AGC}^{i} \left( P_{AGC}^{i} \right) \] The AGC cost of unit \( i \)

\[ F_{SR}^{i} \left( P_{SR}^{i} \right) \] The RSR cost of unit \( i \)

\[ F_{SR}^{i} \left( P_{SR}^{i} \right) \] The SR cost of unit \( i \) in time interval \( t \)

\( \text{Gbest}^{j} \) The optimal solution in particle swarm after iteration \( j \)

\[ P_{i}^{j} \] The power generation of the \( i \)-th unit in time interval \( t \)

\[ r_{1}, r_{2} \] Uniformly distributed random variables between 0 and 1

\[ ST_{i}^{j} \] The startup cost

\[ U_{i}^{j} \] The state of the units in time interval \( t \)

\[ V_{i}^{j} \] Velocity of particle \( i \)

\[ X_{i}^{j} \] Self-optimal solution of particle \( i \) after iteration \( j \)

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