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Parallel GA-PSO Algorithm to Solve the Unit Commitment Problem

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ABSTRACT

The unit commitment (UC) problem has always been considered as one of the main activities by the system planners. Due to the non-linear and complex nature of the UC, different optimization approaches have been presented to solve the problem. In recent years, metaheuristic algorithms have been attracted because of their efficiency to optimize complex problems. This paper combines the concepts of two algorithms, i.e., the particle swarm optimization (PSO) and genetic algorithm (GA) in a parallel manner and proposes a mixed GA-PSO method to optimize the UC problem. The simulation results have justified the effectiveness and advantages of the proposed method, compared to the individual methods.

Keywords: Parallel optimization, Unit commitment, Particle swarm optimization, Genetic algorithm

Introduction

The power generation problem has been focused with several studies due to the increasing load demand all over the world. Increasing the penetration level of different kinds of appliances, transportation facilities and industrialization are the main reasons of these electrifications. Providing the required electricity demand in an economic manner is one of the challenges of the planners. Unit commitment (UC) is an optimization problem for the operation of the power systems. The unit commitment is a problem to optimally determine the on/off status of the generation units, as well as their corresponding production. The aim of the UC is to provide the forecasted load of the system in the specific horizon time with the most economic manner, while all the constraints and system requirements have been overcome [1-4].

Since the UC problems are mixed integer NP-hard, many researches have been done in order to optimize these complex optimization problems. Barani et al. [5] improved the binary quantum-inspired gravitational search technique and introduced a novel method for solving the UC. Ref. [6] solved the UC by considering the penetration of wind generation. Abujarad et al. [7] provided a survey on the UC in the presence of renewable generation units. Different UC models and the presented methods to solve the problem is studies in his paper.

In [8] three methods have been utilized to solve a large scale UC problem that includes charged search system, PSO, and ant colony search.

Several approaches have been presented in order to optimize the UC problem, including [5]:

- Deterministic approaches (such as priority list [9], dynamic programming [10, 11], Lagrangian relaxation [12, 13] and the branch-and-bound method [14]);
- Intelligent approaches (e.g. GA, PSO, simulated annealing [15, 16], quantum inspired evolutionary algorithm [17] and artificial neural networks [18]).

Mirjalili et al. [19] have been introduced GWO (grey wolf optimizer) method by inspiring from the behavior of grey wolves. Afterward, the integrated GWO and PSO is utilized for solving the large-scale UC problems [20]. Panwar et al. [21] have solved a complex UC problem by using the Binary grey wolf optimization (GWO).

One of the important aspects of power systems that should be considered in unit committment is the stochastic nature of electricity demand and electric vehicles charging load. Amini et al. [22] proposed a

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chance-constrained solution that models the probabilistic nature of load demand. Their proposed approach decoupled the electric vehicle charging demand and the conventional load demand to exploit the different patterns and increase the accuracy of estimated load.

Although metaheuristic methods cannot guarantee the optimality of their solutions, due to the complex nature of the UC, these algorithms have been used widely to solve the problem. Indeed, since UC is a large-scale, non-linear (due to the non-linear cost terms and constraints), mixed-integer and non-convex problem (due to the presence of binary variables in order to determine the on/off decisions), generally the deterministic methods are not efficient to solve it [23, 24]. These limitations have encouraged researchers to utilize metaheuristic approaches [7, 25-27].

This paper combines the concepts of PSO and GA in a parallel manner to optimize the UC problem. In fact, the power of PSO and GA to lead the optimization procedure towards the optimum point, as well as their ability to move from the local optimum points to the global solution have been combined with each other to propose a more powerful optimization method.

At the following, the formulations of the UC problem, consisting the objective function and the relevant constraints of the problem is presented. Moreover, the proposed parallel GA-PSO algorithm will be introduced. The numerical analysis section will be provided in order to illustrate the effectiveness and advantages of the parallel GA-PSO. Finally, the concluding remarks have been derived.

Problem Description

a. Objective function

The objective function of the UC has the following cost terms [28]:

- The fuel costs of generating units;
- The start-up costs of the committed units (including hot and cold start-up costs);
- Shut-down costs of decommitted units.

Therefore, it can be formulated by (1).

$$Minimize \quad \left\{\sum_{t=1}^{T}\sum_{j=1}^{N}F_{j,t}\left(p_{j,t}^{0}\right)\times u_{j,t}\right\}+\left\{\sum_{t=1}^{T}\sum_{j=1}^{N}SUC_{j,t}\times u_{j,t}\times\left(1-u_{i,t-1}\right)\right\}+ \left\{\sum_{t=1}^{T}\sum_{j=1}^{N}SDC_{j,t}\times u_{j,t-1}\times\left(1-u_{i,t}\right)\right\}, \quad for \quad j\in N,\ t\in T \tag{1}$$

In which,

$$F_{j,t}\left(p_{j,t}^{0}\right)=\alpha_j+\beta_j\times p_{j,t}^{0}+\gamma_j\times\left(p_{j,t}^{0}\right)^2, \quad for \quad j\in N,\ t\in T \tag{2}$$

where, α_j, β_j and γ_j are fuel cost coefficients of unit *j*.

The start-up costs of the generating units are defined as follows:

$$SUC_{j,t}=\begin{cases}HSC_j, & if \quad MDT_j\le T_j^D\le MDT_j+CST_j\\ CSC_j, & if \quad T_j^D\ge MDT_j+CST_j\end{cases}, \quad for \quad j\in N,\ t\in T \tag{3}$$

b. Problem constraint

The optimization problem should cope with the following constraints [28].

- **Initial state;**

Initial states denote the generation level of a unit, as well as the time that it has been on/off.

- **Power balance restriction;**

$$\sum_{j=1}^{N}p_{i,t}^{0}\times u_{i,t}=D_t, \quad for \quad j\in N,\ t\in T \tag{4}$$

- **Allowable generation levels of the units;**

$$\underline{p_{j,t}}\times u_{j,t}\le p_{j,t}^{0}\times u_{j,t}\le\overline{p_{j,t}}\times u_{j,t}, \quad for \quad j\in N,\ t\in T \tag{5}$$

- **Spinning reserve;**

$$\sum_{j=1}^{N}\overline{p_{j,t}}\times u_{j,t}\ge D_t+SR_t, \quad for \quad j\in N,\ t\in T \tag{6}$$

- **Ramp-up/down constraints of the units;**

$$\begin{cases}p_{j,t}^{0}\le\overline{p_{j,t}}\\ \overline{p_{j,t}}=Min\left\{p_{j,t-1}^{0}+RUR_j,\ \overline{p_j}\right\}\end{cases}, \quad for \quad j\in N,\ t\in T \tag{7}$$

$$\begin{cases}p_{j,t}^{0}\ge\underline{p_{j,t}}\\ \underline{p_{j,t}}=Max\left\{p_{j,t-1}^{0}-RDR_j,\ \underline{p_j}\right\}\end{cases}, \quad for \quad j\in N,\ t\in T \tag{8}$$

- **Start up and shut down constraints of the units;**

$$SUI(j,t)+SDI(j,t)\le 1, \quad for \quad j\in N,\ t\in T \tag{9}$$

- **Prohibited zone;**

The generators may have specific constraints in which they should not be operated in some operating ranges. These restrictions are known as prohibited operating zones. Eq. (10) formulates these constraints. Moreover, these prohibited zones are illustrated in Figure 1.

$$\begin{cases}\underline{p_j}\le p_j^0\le p_{j,1}^{Lower}\\ p_{j,k-1}^{Upper}\le p_j^0\le p_{j,k}^{Lower} & ,k=2,\dots,PZ_j\\ p_{j,PZ_j}^{Upper}\le p_j^0\le\overline{p_j}\end{cases} \tag{10}$$

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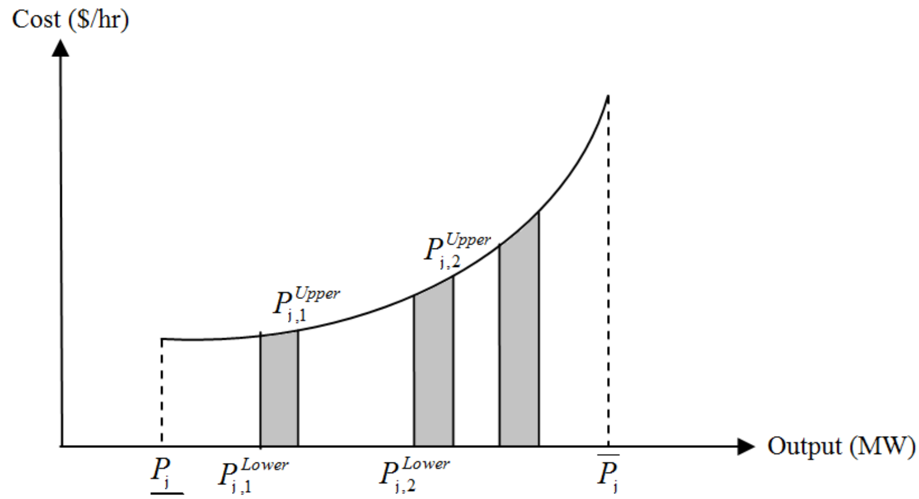

Figure 1. Generators' prohibited zones

- **Minimum up/down time limits (MUT/MDT).**

$$MUT_j \leq T_j^U, \quad for \quad j \in N \qquad (11)$$

$$MDT_j \leq T_j^D, \quad for \quad j \in N \qquad (12)$$

Optimization Algorithm

The metaheuristic methods have been attracted in recent years due to their ability to solve the complex problem. Panwar et al. [22] implemented the binary GWO method to solve the UC. Subba Reddy et al. [30] used the concept of GA to optimize the UC problem. Radial movement optimization (RMO) algorithm is introduced in [31] for the UC. Yu et al. [32] used a Lagrangian relaxation and particle swarm optimization method to find the optimal solution of the UC. In [33], binary successive method and civilized swarm optimization (CSO) approaches are integrated with the aim of solving the UC. A PSO-based method is used in [34] to find the optimum solution of the UC. Kumar et al. [35] used the GA to solve the security constrained UC.

As above-mentioned, the GA and PSO are two metaheuristic algorithms that have been utilized in many researches. GA has been introduced at first by Holland [36] and then is improved by Goldberg [37] and Davis [38]. Compared to other optimization methods, the GA has more ability to move from the local optimum points towards the global solutions.

The PSO is an algorithm that at first introduced by Eberhart and Kennedy by the inspiration of the social behavior of bird flocking or fish schooling [39]. Compared to other intelligent approaches, the PSO has specific advantages (e,g, it is easier for the implementation, conceptually is simpler, and computationally is more efficient) [40-42].

In this paper, with the aim of using the specific advantages of the GA and PSO, the parallel GA-PSO algorithm is used to solve the UC problem. In the proposed approach, each method is responsible to continue the optimization procedure towards better solutions, in the pre-specified iterations. Here, the GA is used to solve the odd iterations, while the PSO solves the even iteration numbers. The results that are achieved by using one of the methods will be considered as the input to the second algorithm for the next iteration. The second algorithm will continue the optimization procedure of the first one. Therefore, the parallel GA-PSO uses the advantage of both the methods to better scape from the local optimum points and converge to better solutions. The procedure of the proposed parallel GA-PSO method is illustrated in Figure 2.

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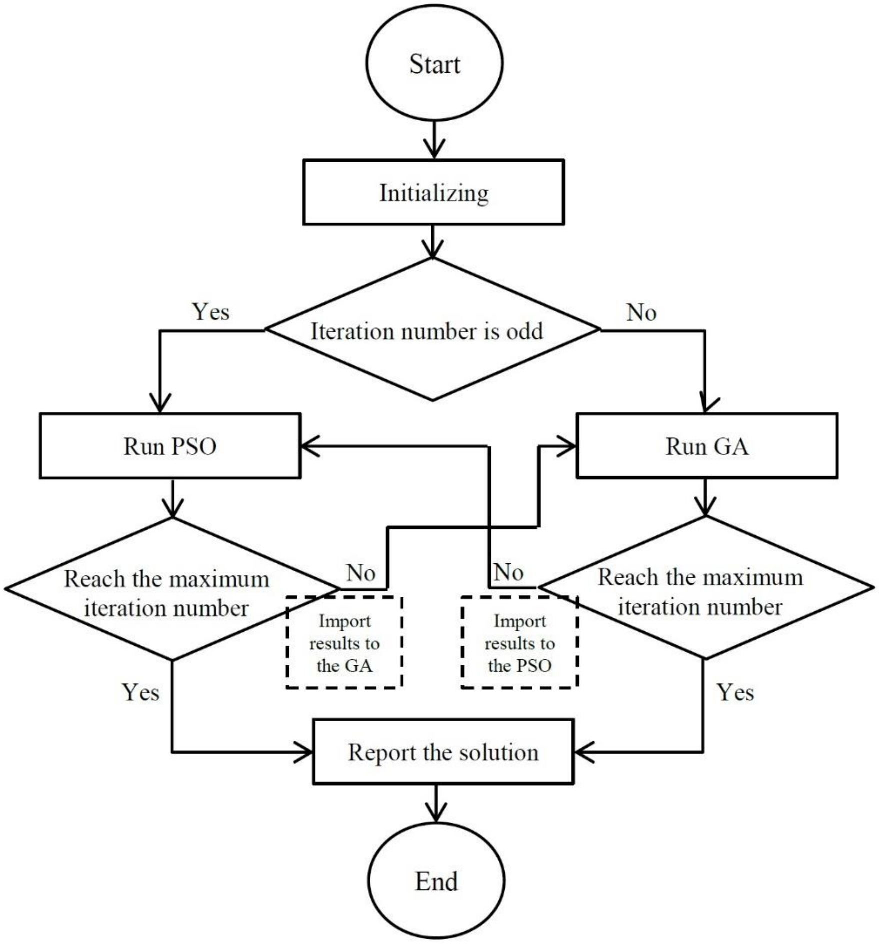

Figure 2. The flowchart of the parallel GA-PSO algorithm

Simulation Results

A conventional 10-unit test system [28] is utilized here to investigate the performance and advantages of the proposed method. The scheduling time of the UC is assumed to be 24 hours. All the generation units and demand data are driven from [28]. However, the system demand, generators operation data and their cost coefficients are provided in Tables 1-3 for the ease of access.

In order to compare the advantages of GA-PSO, three different scenarios are considered. The first scenario solves the UC problem by using the GA algorithm. In the second scenario, the problem is optimized by using the PSO algorithm. Finally, the proposed parallel GA-PSO method is employed in the third scenario.

Tables 4 and V are provided to illustrate the results of the UC that are derived by using the GA-PSO. Table 4 compares the results of the GA-PSO and GA algorithms. The differences in the units' on/off statuses are highlighted in this table (the bolded and highlighted cells in this table indicates the changes between the results of the GA and GA-PSO). As an example, it is observed in Table 4 that unit 8 is off as a result of the GA-PSO, while it was selected to be on by the GA method. The objective functions of the first and third scenarios are 631667.6166 [$] and 609473.0067 [$], respectively, that shows 22194.6099 [$] cost reduction by using the GA-PSO (3.51 percent cost reduction).

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Table 1
The demand of the test system

Hour	Demand (MW)	Hour	Demand (MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

Table 2
Generators' data

Units	$\overline{P}$ (MW)	$\underline{P}_{i,t}$ (MW)	MUT (hr)	MDT (hr)	SC ($)	IC (hr)
Unit_01	455	150	8	8	4500	8
Unit_02	455	150	8	8	5000	8
Unit_03	130	20	5	5	550	-5
Unit_04	130	20	5	5	560	-5
Unit_05	162	25	6	6	900	-6
Unit_06	80	20	3	3	170	-3
Unit_07	85	25	3	3	260	-3
Unit_08	55	10	1	1	30	-1
Unit_09	55	10	1	1	30	-1
Unit_10	55	10	1	1	30	-1

Table 3
Generators supply curves' coefficients

Coefficients	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
α	0.00048	0.00031	0.002	0.00211	0.00398
β	16.19	17.26	16.6	16.5	19.7
γ	1000	970	700	680	450
Coefficients	**Unit 6**	**Unit 7**	**Unit 8**	**Unit 9**	**Unit 10**
α	0.00712	0.0079	0.00413	0.00222	0.00173
β	22.26	27.74	25.92	27.27	27.79
γ	370	480	660	665	670

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Table 4
The comparison results of the GA-PSO and GA

Unit \ Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1
5	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1
6	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0
7	1	1	1	1	1	0	0	0	0	1	1	1	1	**0**	0	0	0	1	1	1	1	0	0	0
8	**0**	**0**	0	1	1	1	0	1	1	0	1	0	1	**0**	1	**0**	1	0	1	1	1	**0**	**0**	**0**
9	1	**0**	0	1	**0**	1	0	0	**0**	1	1	1	1	**0**	1	1	0	1	**0**	1	1	**0**	1	1
10	1	1	1	1	**0**	1	**0**	1	1	1	1	1	**0**	**0**	1	0	1	0	**0**	1	1	**0**	1	0

Moreover, Table 5 compares the results of the GA-PSO and PSO algorithms. The objective functions of the second and third scenario are 630210.0148 [$] and 609473.0067 [$], respectively, that shows 20737.0081 [$] cost reduction by implementing the propose method (3.29 percent cost reduction). All the differences in the units' statuses as the results of the GA-PSO and PSO are determined by the bolded and highlighted cells of Table 5. For instance, as the result of the GA-PSO, unit 9 is off, while it was determined to be on by using the PSO.

Table 5
The comparison results of the GA-PSO and PSO

Unit \ Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1
5	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1	1
6	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0
7	1	1	1	1	1	0	0	0	0	1	1	1	1	**0**	0	0	0	1	1	1	1	0	0	0
8	**0**	**0**	0	1	1	1	0	1	1	0	1	0	1	**0**	1	**0**	1	0	1	1	1	**0**	**0**	**0**
9	1	**0**	0	1	**0**	1	0	0	**0**	1	1	1	1	0	1	1	0	1	**0**	1	1	**0**	1	1
10	1	1	1	1	**0**	1	**0**	1	1	1	1	1	**0**	**0**	1	0	1	0	**0**	1	1	**0**	1	0

All the results prove that the parallel GA-PSO method is more different than other individual algorithms. 20 cells in Table 4 and 19 cells in Table 5 are highlighted as the differences between the GA-PSO solution and the results of the individual GA and PSO methods. As another example to show the better performance of the GA-PSO compared to the individual methods, it is observed that unit 8 is off in the solution of the GA-PSO, while it was determined on by other methods. Indeed, due to the lower cost coefficients of unit 4 than unit 8, the generation of unit 4 is increased during these hours instead of keeping on the unit 8.

Figure 3 illustrated the convergence of three methods to find the optimal solutions. As shown in this figure, the best objective function is obtained by the GA-PSO algorithm. Trends of these algorithms show that GA-PSO could be converged in a lower number of iterations. According to Figure 3, it could be observed that the parallel GA-PSO has the benefits of both the GA and PSO algorithms. As it is shown, the GA has a very important role to lead the GA-PSO procedure to move towards a better solution in the "657th" iteration. Moreover, there are changes that have been applied by the PSO in even iteration numbers of the GA-PSO to lead the optimization procedure to find better and better solutions. Therefore, the specific advantages of the GA and PSO are combined in the GA-PSO method to help the optimization procedure to find better solutions with lower iteration numbers.

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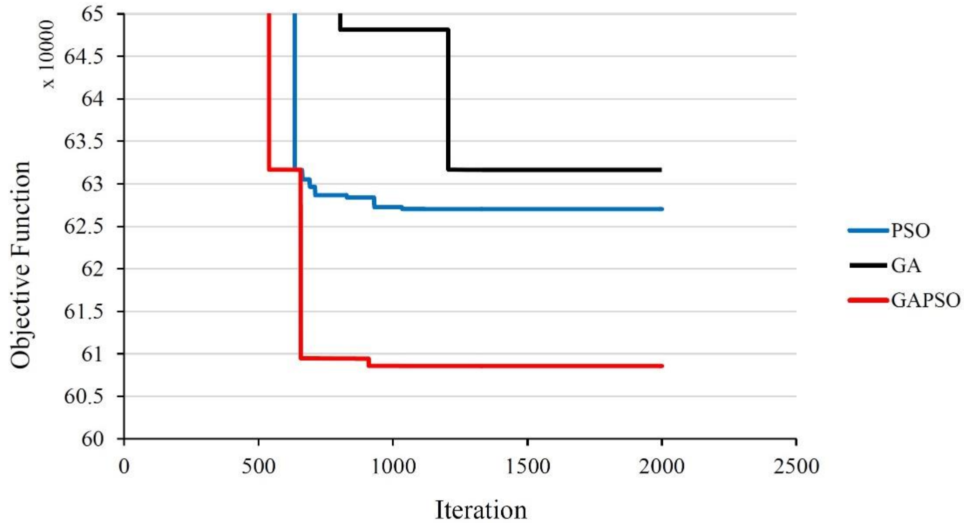

Figure 3. The results of three scenario.

Conclusion

The paper addressed the UC problem as one of the main concerns in the context of power grids. Due to the non-linearity and complexity of the problem, many techniques have been developed to optimize the UC. Here, a parallel GA-PSO method is proposed to efficiently solve the UC. The developed algorithm utilizes the features and advantages of both the PSO and GA to lead the optimization procedure towards a better solution (to move from the local optimal points to achieve better solutions). A test system is utilized to employ the proposed method and show the effectiveness and efficiency of it.

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Nomenclature

Indices	
j	Generators;
k	Generators' prohibited zones;
t	Scheduling time;
Constants	
$SUC_{i,t}/SDC_{i,t}$	Start-up/Shut-down costs of the j^{th} unit at hour t [$/each switching];
N	Number of units;
T	Horizon time;
HSC_j/ $CSCj$	Hot/Cold start-up costs [$ per each hot/cold start-ups];
MDT_j/MUT_j	Minimum down-time/Minimum up-time of unit number j [hour];
D_t	Demand at time t [MW];
$\underline{P_{j,t}} / \overline{P_{j,t}}$	Minimum/Maximum generation limits of j^{th} unit at time t [MW];
SR_t	Amount of spinning reserve at time t [MW];
RUR_j/RDR_j	Ramp up/Ramp down rates of unit number j [MW/hour];
PZ_j	Number of prohibited zones of the unit j;
$p_{j,k}^{Lower} / p_{j,k}^{Upper}$	Lower/Upper bounds of the K^{th} prohibited zone of j^{th} unit [MW];
Variables	
$P_{j,t}^{0}$	Generation of j^{th} unit at time t [MW];
$u_{j,t}$	On/off statuses of j^{th} unit at time t; in which, 1 is on and 0 is off;
T_j^U / T_j^D	Time durations that the j^{th} unit is continuously on/off [hour];
SUI/SDI	Start-up/Shut-down indicators;
Functions	
$F_{j,t}$	Supply curve of the j^{th} unit;

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