Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2015, Article ID 710876, 13 pages
http://dx.doi.org/10.1155/2015/710876

Research Article

A Hybrid Search Algorithm for Midterm Optimal Scheduling of Thermal Power Plants

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Received 9 September 2014; Revised 7 January 2015; Accepted 26 April 2015

Academic Editor: Andrzej Swierniak

A hybrid search algorithm consisting of three stages is presented to solve the midterm schedule for thermal power plants (MTSFTPP) problem, where the primary objective is to achieve equal accumulated operating hours of installed capacity (EAOHIC) for all thermal power plants during the selected period. First, feasible spaces are produced and narrowed based on constraints on the number of units and power load factors. Second, an initial feasible solution is obtained by a heuristic method that considers operating times and boundary conditions. Finally, the progressive optimality algorithm (POA), which we refer to as the vertical search algorithm (VSA), is used to solve the MTSFTPP problem. A method for avoiding convergence to a local minimum, called the lateral search algorithm (LSA), is presented. The LSA provides an updated solution that is used as a new feasible starting point for the next search in the VSA. The combination of the LSA and the VSA is referred to as the hybrid search algorithm (HSA), which is simple and converges quickly to the global minimum. The results of two case studies show that the algorithm is very effective in solving the MTSFTPP problem accurately and in real time.

1. Introduction

Electric power generation in China mainly consists of coal-fired thermal power plants and hydroelectric power plants [1, 2]. At the end of 2013, China's total installed generation capacity reached 12473.8 GW, with approximately 64.2% derived from coal-fired thermal power plants, 5% from thermal power using other fuels (e.g., oil and gas), 22.5% from hydropower, 6.1% from wind power, 1.2% from nuclear power, and the remainder from other sources [2]. However, coal-fired units are difficult to start up and shut down, and they respond slowly to system demand because preheating and cooling of the stream turbines is required. Moreover, startup and shutdown of a coal-fired unit require considerable amounts of fuel [3]. Therefore, thermal plants are usually scheduled to meet the base demand to ensure that the generation process proceeds smoothly and to minimize the startup and shutdown times of thermal units.

Over the past decade, extreme weather events such as storms, droughts, high temperatures, and damaging hail have occurred frequently in China, which has caused the demand on power systems to change substantially from day to day. These large deviations in demand over short periods cause difficulties in the scheduling of the power systems, a problem that is exacerbated by the large number of coal-fired thermal units in use. Consequently, the power dispatch centers in China must determine the optimal midterm schedule for thermal power plants (MTSFTPP), where "midterm" is a period of one to six months, to determine which units to start up and shut down or the boot capacity of every thermal plant each day before determining the short-term and daily schedules.

The midterm schedule is important for the economical operation of power systems. The objective of the scheduling problem is to find the optimal set of thermal generating units in a power system that will satisfy the system demand, operational restrictions, reliability constraints, and security requirements for each period considered. Unlike the short-term unit commitment problem associated with power systems, which involves determining a startup and shutdown schedule of units to meet the demand over a period of one day to one week, loads must be dispatched to each plant in the midterm to allow for maintenance and coordination with hydropower plants. Optimal midterm scheduling smoothes the demand on thermal plants, allowing them to operate more efficiently, and makes the best use of hydropower plants. In contrast with the short-term optimal scheduling of thermal power plants, there has been little research on the midterm problem.

The MTSFTPP problem is a variation of the unit commitment (UC) problem, which is a large-scale, nonlinear, nonconvex, mixed-integer combinatorial optimization problem. Various techniques [4–8] have been used to solve this computationally expensive problem [5]. Among these techniques are dynamic programming (DP) [9–12], branch-and-bound (BAB), Lagrangian relaxation (LR) [13–15], integer programming (IP) [16, 17], and metaheuristic algorithms such as genetic algorithms (GA) [18–24], particle swarm optimization (PSO), and neural networks [25–27].

Many methods such as DP, BAB, and IP suffer from the curse of dimensionality; that is, the solution space increases exponentially with the number of generating units. As a result, the computation time becomes unacceptable. LR, which decomposes the primal problem into a set of single plant or unit optimization subproblems that are easier to solve independently, has shown potential in solving the UC problem. However, this approach requires the conversion of the optimal dual solution into a feasible solution of the primal problem because of the duality gap, which represents the primary difficulty associated with LR. Metaheuristic algorithms have been widely used to solve the UC problem in recent years, but the quality of the solution depends on the choice of the control parameters, and choosing the control parameters of these algorithms is a very difficult task.

Essentially, the MTSFTPP problem is a multistage (in this context, the term "stage" refers to time) decision problem with unit constraints (type 1), thermal power load factor constraints (type 2), operating time constraints (type 3), and boundary condition constraints (type 4). Considering that types 1 and 2 are single-stage constraints and independent between any two stages, whereas type 4 constraints can be met by the initial solution, the optimization process mainly involves type 3 constraints, which are time constraints. This study investigates a hybrid search algorithm (HSA) to solve the MTSFTPP problem. The primary objective is to achieve equal accumulated operating hours of installed capacity [25] (EAOHIC) for all thermal power plants over a given period, with extra hours that are given to the plants with lower emissions, higher efficiency, and occasional unit maintenance. A more detailed description of the problem is provided in Section 2. Section 3 presents a detailed explanation of the HSA. A case study is presented in Section 4, and conclusions are presented in Section 5.

2. Problem Formulation

2.1. Objective Function. Equality, impartiality, and transparency are important in electric power dispatching. Based on power system security, stability, and economics, units should be treated equally in problems involving operations management and information disclosure. In many western countries, the driving force behind deregulation is the belief that competitive markets make the industry more efficient, leading to lower costs. In the case of China, similar to other developing countries, the incentive for restructuring is derived from the desire to provide equal opportunities to all participants. In China, the firms established by the government are responsible for power system operations, and the power systems are operated in an integrated fashion. Therefore, equality is usually the main concern in long-term and midterm scheduling in China. In this study, EAOHIC is the primary consideration in the MTSFTPP problem. Operating hours are accumulated from the beginning of the respective warm-up periods to the end of the computational period (Figure 1). The EAOHIC constraint for the MTSFTPP problem is formulated as follows:

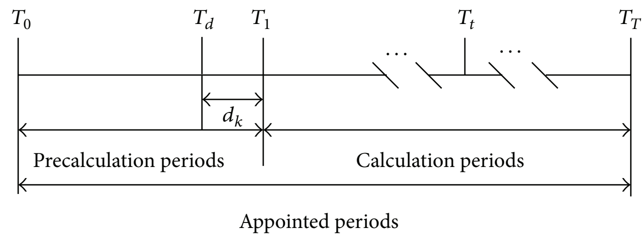

Figure 1: Accumulated operating hours defined from the start of the warm-up period to the end of the computational period (horizon).

$$H_i = H_j \quad (i \neq j), \tag{1}$$

where H_i, H_j are the accumulated operating hours of installed capacity for plants i, j, respectively, in the selected period.

Although the concept captured by (1) is unambiguous and easily understood, the problem is very difficult to solve directly because the formulation is related to all plants and the objective cannot be evaluated by the computation of a single mathematical expression. Considering that the variance can be used to describe the degree of dispersion of data, let $H = (H_1, H_2, \ldots, H_k, \ldots, H_m)$ be the set of accumulated operating hours of the installed capacity for the plants, and let $D(H)$ be the variance of the set H. Equation (1) can be replaced by the following problem:

$$\begin{aligned} f &= \min D(H), \\ D(H) &= \frac{1}{m}\sum_{k=1}^{m}\left(H_k - \overline{H}\right)^2, \\ \overline{H} &= \frac{1}{m}\sum_{k=1}^{m} H_k, \\ H_k &= H_{kp} + H_{kT} - H_{ke}, \\ H_{kT} &= \frac{1}{N_k} * \overline{C}_k * T * 24 * r, \\ \overline{C_k} &= \frac{1}{T}\sum_{t=1}^{T} C_{kt}, \end{aligned} \tag{2}$$

where the variables are defined as follows: H is the set of H_k, the accumulated operating hours of the installed capacity of plant k during the selected period, in hours (h); m is the total number of plants; $D(H)$ is the variance of set H, in h^2; $\overline{H}$ is the average of set H, in h; H_{kp} is the operating hours of installed capacity of plant k accumulated during the warm-up period, in h; H_{kT} is the operating hours of installed capacity of plant k accumulated during the computational period, in h; H_{ke} is the extra hours assigned to plant k, in h; T is the total number of steps t in the computational period, where each step is one day; N_k is the installed capacity of plant k, in MW; $\overline{C_k}$ is the average of the operating capacity of plant k during the computational period, in MW; r is the load factor; and C_{kt} is the operating capacity of plant k in period t, in MW.

2.2. Constraints. Due to the operational requirements, the minimization of the objective function is subject to the following types of constraints.

(1) Unit Constraints. Consider

$$u_{t,k}^{\min} \le u_{t,k} \le u_{t,k}^{\max}, \quad (3)$$

where $u_{k,t}^{\min}$ and $u_{k,t}^{\max}$ are the minimum and maximum numbers of units, respectively, in plant k in period t and $u_{k,t}$ is the number of active units in plant k in period t.

(2) Thermal Power Load Factor Constraints. Consider

$$C_{st} * r^{\min} \le P_t \le C_{st} * r^{\max}, \quad (4)$$

where C_{st} is the operating capacity of the system in period t, in MW, and $r^{\min}$ and $r^{\max}$ are the minimum and maximum load factors of thermal power, respectively, which are calculated from the long-term real-world operation of power grid. P_t is the demand of system in period t, in MW.

(3) Time Constraints. Midterm optimal thermal power plant scheduling only dispatches the system load to the plants and does not distribute the load among the units in each plant. Therefore, we transform the constraints on the response of a plant into minimum-time constraints at minimum or maximum output. Consider

$$\begin{aligned} \tau_{k,j}^{\text{peak}} &\ge T_k^{\text{peak,min}}, \\ \tau_{k,j}^{\text{valley}} &\ge T_k^{\text{valley,min}}, \end{aligned} \quad (5)$$

where $\tau_{k,j}^{\text{peak}}$ is the duration of peak j in the output of plant k, $T_k^{\text{peak,min}}$ is the minimum duration of the peak in the output of plant k, $\tau_{k,j}^{\text{valley}}$ is the duration of valley j in the output of plant k, and $T_k^{\text{valley,min}}$ is the minimum duration of the valley in the output of plant k.

(4) Boundary Condition Constraints. The planning for the current period depends on the previous states of the units. For the plant k, considering the previous period d_k as the maximum in $T_k^{\text{peak,min}}$ and $T_k^{\text{valley,min}}$, the states of the units before the starting point affect the operation of the units through the minimum peak and valley time restrictions, as shown in Figure 1. Consider

$$\begin{aligned} \tau_{k,0}^{\text{peak}} &\ge T_k^{\text{peak,min}}, \\ \tau_{k,0}^{\text{valley}} &\ge T_k^{\text{valley,min}}, \end{aligned} \quad (6)$$

where $\tau_{k,0}^{\text{peak}}$ and $\tau_{k,0}^{\text{valley}}$ are the first duration of peak and valley in the output of plant k, respectively.

Note that the boundary condition constraints are the same as the time constraints (type 3), the time constraints considering the time horizon in $[T_1, T_T]$, while the boundary condition constraints considering in $[T_d, T_T]$.

3. Solution Methodology

The MTSFTPP problem is a UC problem, and each approach to the problem has its disadvantages, as mentioned previously. Constraints of types 1 and 2 involve a single period and can be treated independently to reduce the search space, constraints of type 4 can be satisfied in the initial solution, and constraints of type 3 must be satisfied over multiple periods. This study investigates a novel method using three stages to solve the problem.

3.1. Producing a Feasible Solution Space Satisfying Constraint Types 1 and 2. Mathematically, the MTSFTPP problem, like the UC problem, suffers from the curse of dimensionality as the number of units and the computational period increases. Thus, it is difficult to solve this problem by considering a simple combination of units. For a power grid with five thermal plants, each having four units, the total number of unit combinations will reach 8.67×10^{41} for a horizon of one month, and the search will be computationally expensive. Fortunately, the actual constraints on the thermal power load factors and the number of units are beneficial because they reduce the search space when searching for feasible solutions. The specific procedure is as follows.

Step 1. For the thermal plants with different values of unit capacity, each plant will be represented by several "virtual plants" whose capacity depends on the number of units of a given type. For instance, for a thermal plant with 5 units, including 2 units with 300 MW of capacity and 3 units with 200 MW of capacity, the plant will be divided into 2 "virtual plants." By initializing the plants in this manner, the final number of virtual plants will be greater than the number of actual plants and will be denoted as M.

Step 2. Start from the first period; that is, let $t = 1$.

Step 3. Sort the combinations U_t that meet the unit constraints in period t; that is, $U_t = \{u_t^1, u_t^2, \ldots, u_t^i, \ldots, u_t^{N_{Ut}}\}$ ($i = 1 \sim N_{Ut}$), where N_{Ut} is the number of combinations that meet constraint 1 (3) in period t, $u_t^i = (u_{t,1}^i, u_{t,2}^i, \ldots, u_{t,k}^i, \ldots, u_{t,M}^i)$, $u_{k,t}^{\min} \le u_{k,t}^i \le u_{k,t}^{\max}$ ($k = 1 \sim M$).

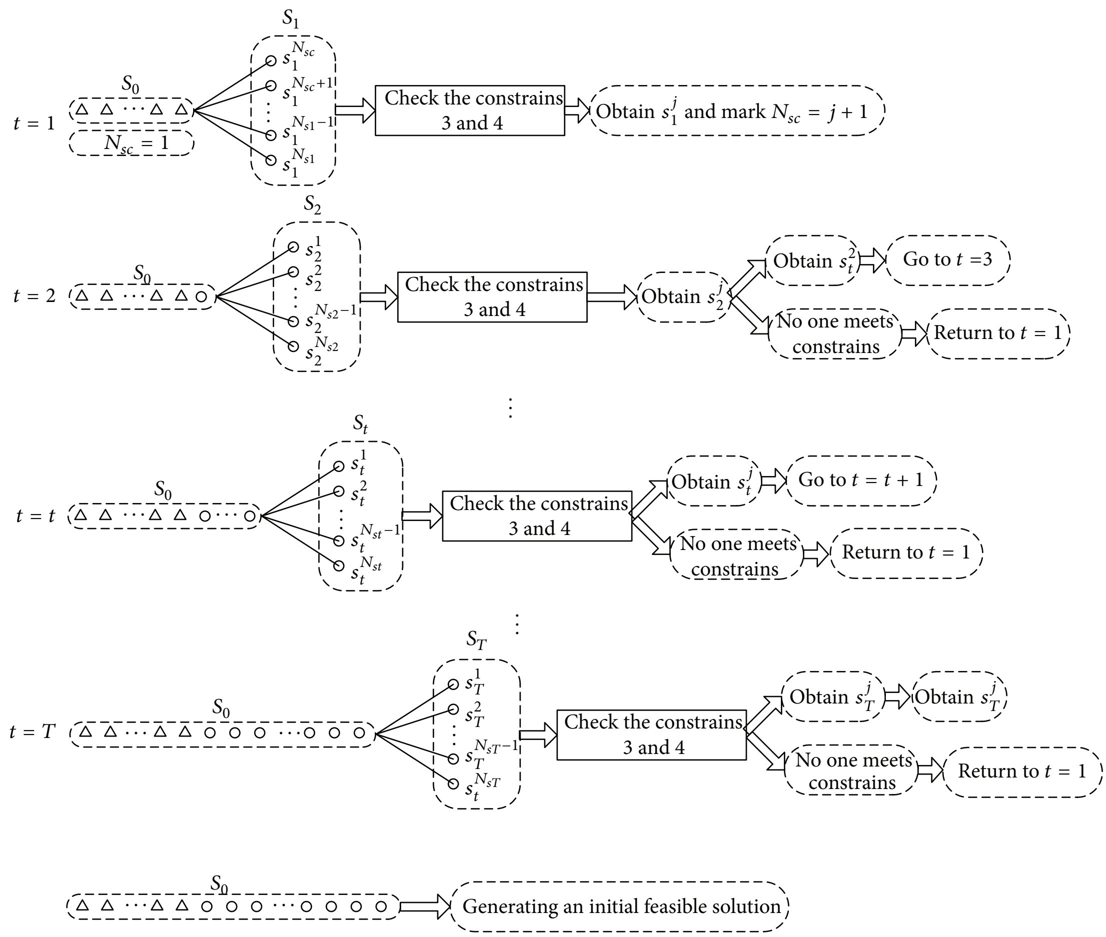

Figure 2: The procedure for generating an initial feasible solution.

Step 4. Select the combinations S_t that satisfy the thermal power load factor constraints from U_t in period t; that is, $S_t = \{s_t^1, s_t^2, \ldots, s_t^j, \ldots, s_t^{N_{st}}\}$ $(j = 1 \sim N_{st})$, where N_{st} is the number of combinations that satisfy constraints 1 and 2 ((3) and (4)) in period t.

Step 5. If $t < T$, set $t = t + 1$ and return to Step 3. Otherwise, stop and retain the feasible solution space $S = \{S_1, S_2, \ldots, S_t, \ldots, S_T\}$ satisfying constraints 1 and 2 ((3) and (4)).

3.2. Generating an Initial Feasible Solution Using a Heuristic Method. At this point, we have obtained the feasible space satisfying constraints of types 1 and 2. Finding the optimum in the next stage requires a solution that satisfies all of the operational and system constraints. A heuristic method is proposed for this goal. The procedure is as follows.

Step 1. Obtain the operating data for d days before the starting point. These data will be stored in an array and denoted as the scheme S_0. The midterm schedule must satisfy the boundary constraints (type 4) between actual operation and future scheduling.

Step 2. Start from the first period; that is, let $t = 1$.

Step 3. Obtain all combinations S_t for period t $(t = 1 \sim T)$ using the method described in Section 3.1.

Step 4. Choose a combination that satisfies constraint type 3 in (5) and that is suitable for the boundary constraints, type 4. For each subset s_t^j $(j = 1 \sim N_{st})$ in combination space S_t at period t, check the type 3 and type 4 constraints. In particular, the type 4 constraints use the historical data S_0 to satisfy the minimum-time constraints at the starting points. Clearly, S_0 includes the historical data when $t = 1$. The search is stopped and the current subset appended to S_0 when a feasible subset is found for all subsets s_t^j $(j = 1 \sim N_{st})$. The subset number in the first period is stored to reduce the search in the next cycle. In this case, continue to the next period and set $t = t + 1$. Otherwise, return to the first period, start from the stored number, and repeat the previous procedure. An initial feasible solution will be generated for the optimization.

A flow chart and pseudocode for generating an initial feasible solution are shown in Figure 2 and Algorithm 1, respectively.

```
Heuristic for generating an initial feasible solution
Input actual operation data for d days before the start point S_0 = {S_01, ..., S_0k, ..., S_0M}
feasible solution space S = {S_1, ..., S_t, ..., S_T}, S_t = {s_t^1, ..., s_t^j, ..., s_t^{N_st}}, s_t^j = (u_t1^j, ..., u_tk^j, ..., u_tM^j)
initial N_sc = 1
Output initial feasible solution I
for all periods from t = 1 to T
  for all the feasible states s_t^j ⊂ S_t from j = b to N_st
    if t = 1
      b = N_sc
    end if
    else
      b = 1
    end else
    Define num to count, num = 0
    for all plants states u_tk^j ∈ s_t^j from k = 1 to M
      if τ_{k,j}^peak(S_0k, u_tk^j) ≥ T_k^{peak,min} & τ_{k,j}^valley(S_0k, u_tk^j) ≥ T_k^{valley,min}
                                          num = num + 1
      end if
    end for
    if num = M
      Expand S'_0 by appending s_t^j to S_0
        Store s_t^j in I
        if t = 1
          N_sc = j + 1
        end if
    end if
    if num < M & j = N_st
      t = 1, j = N_sc,
    end if
  end for
end for
```

Algorithm 1: Algorithm for generating an initial feasible solution.

3.3. Hybrid Search Algorithm. Numerous operational and system constraints are imposed in the unit commitment problem. The aforementioned initial feasible solution meets only some constraints, and the optimization for unit commitment still must be performed. Sections 3.3.1 and 3.3.2 present a two-step procedure for optimization.

3.3.1. Vertical Search Algorithm. Over the past few decades, the progressive optimality algorithm [28] (POA) has been shown to have great advantages over classical optimization methods and has been one of the most widely used techniques for hydroelectric generator scheduling and water resources problems [29–31]. The POA attempts to find the best solution in a given decision space based on Bellman's Principle and is free of a particular model structure. The advantages of the POA over other optimization techniques are that it can decompose a multistate decision problem into several nonlinear programming subproblems to reduce the dimensionality. In fact, the optimal scheduling of thermal power plants is a multistate and multistage problem, and hence it is suitable for the POA. The POA is defined as follows [27]:

$$f = \min \sum_{t=1}^{T} g\left(x_{t-1}, x_t\right),$$
$$G\left(x_{t-1}, x_{t+1}\right) = \min_{1 \le j \le N_t} \left[g\left(x_{t-1}, x_t^j\right) + g\left(x_t^j, x_{t+1}\right)\right], \tag{7}$$

where x_t^j is the state j in period t, $G(x_{t-1}, x_{t+1})$ is the objective function in period t, and x_{t-1} and x_{t+1} are the decision variables in periods $t-1$ and $t+1$, respectively. For the optimal scheduling of thermal power plants, the problem can be mathematically stated as follows:

$$f = \min D(H),$$
$$G\left(s_t, s_{t+1}\right) = \min_{1 \le j \le N_{st}} \left[D\left(H\left(s_t^j, s_{t+1}\right)\right)\right] \quad 1 \le t < T,$$
$$G\left(s_{t-1}, s_t\right) = \min_{1 \le j \le N_{st}} \left[D\left(H\left(s_{t-1}, s_t^j\right)\right)\right] \quad t = T, \tag{8}$$

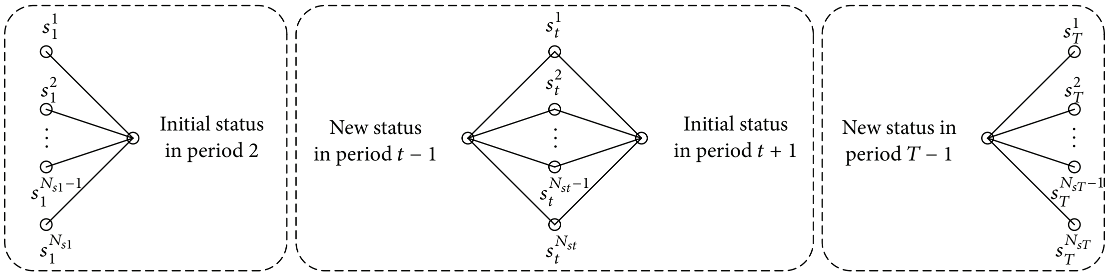

Figure 3: Search principle of VSA using POA.

VSA
Input initial feasible solution $I = \{I_t \mid I_t \subset S_t, 1 \le t \le T\}$, $I_t = (i_{t1}, \ldots, i_{tk}, \ldots, i_{tM})$
actual operation data for d days before the start point $S_0 = \{S_{01}, \ldots, S_{0k}, \ldots, S_{0M}\}$
feasible solution space $S = \{S_1, \ldots, S_t, \ldots, S_T\}$, $S_t = \{s_t^1, \ldots, s_t^j, \ldots, s_t^{N_{st}}\}$, $s_t^j = (u_{t1}^j, \ldots, u_{tk}^j, \ldots, u_{tM}^j)$
initial value V_0
Output optimized solution
for $n = 1$ to N
  for all periods from $t = 1$ to T
    for all the feasible states $s_t^j \subset S_t$ from $j = 1$ to N_{st}
      Define num to count, num = 0
      for all plants states $u_{tk}^j \in s_t^j$ from $k = 1$ to M
        if $\tau_{k,j}^{\text{peak}}(S_{0k}, u_{tk}^j) \ge T_k^{\text{peak,min}}$ & $\tau_{k,j}^{\text{valley}}(S_{0k}, u_{tk}^j) \ge T_k^{\text{valley,min}}$
          num = num + 1
        end if
      end for
      if num = M
        Calculate $V = D(H)$
        if $V < V_0$
          Replace i_{tk} using u_{tk}^j; $V_0 = V$
        end if
      end if
    end for
  end for
  Obtain new solution R
  If I = R
    Obtain optimized solution
  end if
end for

Algorithm 2: Algorithm for VSA.

where $H(s_t^j, s_{t+1})$ and $H(s_{t-1}, s_t^j)$ are functions that give the operating hours of installed capacity when the status is s_t^j and $G(s_t, s_{t+1})$ and $G(s_{t-1}, s_t)$ are the objective functions for period t. With this formulation, we choose s_t^j from S_t with the status in the other periods fixed to obtain the optimal objective function value. A diagram of the operating of the POA is shown in Figure 3, and pseudocode for the algorithm is shown in Algorithm 2.

The aforementioned search is a sequential procedure, which we refer to as the vertical search algorithm (VSA), as distinguished from the following search algorithm.

3.3.2. Lateral Search Algorithm. The solution obtained using the VSA is clearly affected by the starting point (i.e., initial guess) and can converge to a local minimum. Hence, another search strategy is presented to improve the solution by enlarging the search space. The search addresses the objective that all plants have equal or approximately equal operating hours of installed capacity. To attain this goal, the plants whose operating hours are greater than or less than the average value will be adjusted. The plant with the greatest bias from the average is selected for adjustment. Generally, we choose the periods of maximum or minimum plant output to perform the adjustments. This state involves situations in which the system load allows for a change in the number of active units. Another state occurs in periods of maximum or minimum output during which a change in the number of active units in other periods is not possible. For the first case, the adjustment is started from the first period among the periods

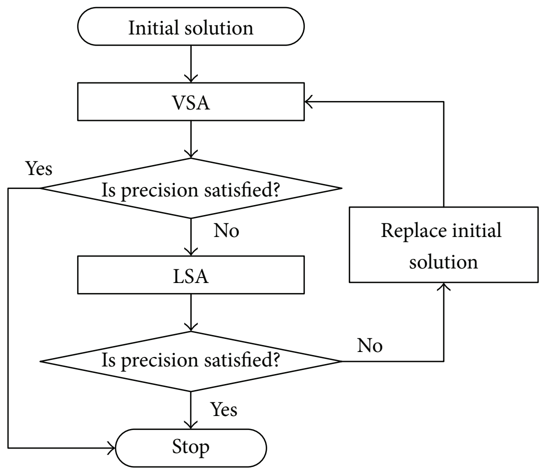

Figure 4: Search procedure for HSA using VSA and LSA.

of maximum or minimum output. The increase or decrease in the number of units depends on the difference from the average and the constraints. If the plant's operating hours of installed capacity are greater than the average, we decrease the number of units for selected periods. This adjustment is a trial procedure because of the complex constraints and because the starting period for the adjustment is related to the constraints. For the second case, the changes in the maximum/minimum output periods will cause a change in the unit status in subsequent periods due to the minimum-time constraints. The adjustment features two aspects: satisfying all of the constraints in the maximum- or minimum-output periods and satisfying the constraints in subsequent periods. In either case, a new feasible solution will be produced. Consequently, an updated optimal solution can be obtained using the VSA. Herein, we refer to the search procedure as the lateral search algorithm (LSA). An optimal solution that satisfies the constraints can be obtained using the VSA and LSA alternately. A flowchart for the hybrid search algorithm that combines the VSA and LSA is shown in Figure 4.

4. Case Study

The proposed method was applied to the MTSFTPP problem for an actual power system, the Yunnan Power Grid (YPG) in China. Currently, it is used as the primary tool to determine the midterm optimal scheduling of thermal power plants by the operators of YPG. Yunnan is among the richest in hydropower resources of all of the provinces in China. Its potential hydropower capacity is 103.6 GW, which contributes 15.3% of the national capacity and ranks third in the nation. The exploitable hydropower capacity is 90 GW, which contributes 17.9% and ranks second in the nation. By the end of 2013, the total installed capacity of the YPG had reached 26.1 GW, with hydropower capacity accounting for 16.7 GW and thermal capacity accounting for 8.935 GW. Proper scheduling of thermal power plants can make the best use of hydropower systems and improve system security.

Table 1: Thermal power system in the YPG.

Plant number	Units (number ∗ capacity, MW)	Capacity (MW)
1	4 ∗ 600	2400
2	6 ∗ 300	1800
3	4 ∗ 300	1200
4	2 ∗ 200 + 2 ∗ 300	1000
5	2 ∗ 300	600
6	2 ∗ 300	600
7	2 ∗ 300	600
8	2 ∗ 300	600
9	1 ∗ 135	135

The thermal power system in the YPG consists of 9 thermal power plants with a total installed capacity of 8.935 GW and 27 units. The dispatching center in the YPG controls the thermal power system. Table 1 lists the basic data for these plants. The HSA was implemented in Java and executed on a PC with an Intel Core 2 Duo 2.93 GHz CPU and 2 GB of memory. An actual schedule for 2013 in the YPG was used to test the validity and the computational efficiency of the proposed method.

Two typical months, May and September, were selected to demonstrate the practicality and the efficiency of the method. May represents the beginning of the flood season, when the hydropower plants can operate at their peak and the demand on the thermal system can be decreased. Conversely, September represents the beginning of the dry season, when the hydropower system has the lowest output and the demand on the thermal system increases.

According to the real-world operating experience and users' actual demands, the basic parameters for the HSA are set as follows:

(i) minimum load factor $r^{\min} = 0.7$;

(ii) maximum load factor $r^{\max} = 0.9$;

(iii) initial load factor $r = 0.8$;

(iv) actual operating hours of installed capacity in the warm-up period $H_{kp} = 0$ ($k = 1 \sim 9$);

(v) extra hours $H_{ke} = 0$ ($k = 1 \sim 9$);

(vi) minimum number of units $u_{kt}^{\min} = 1$ ($k = 1 \sim 8$, $t = 1 \sim T$), and $u_{kt}^{\min} = 0$ for $k = 9$;

(vii) maximum number of units $u_{k,t}^{\max} = UA_{k,t}^{\max}$ ($k = 1 \sim 9$, $t = 1 \sim T$), where $UA_{k,t}^{\max}$ is the number of available units for plant k in period t;

(viii) minimum duration of peak in plant output $T_k^{\text{peak},\min} = 7$ days ($k = 1 \sim 9$);

(ix) minimum duration of valley in plant output $T_k^{\text{valley},\min} = 3$ days ($k = 1 \sim 9$);

(x) considering previous periods $d_k = 7$ days ($k = 1 \sim 9$).

The average cost time of 10 runs for May is 9764 ms and for September is 10241 ms, and the calculation efficiency can be met the actual demand in midterm scheduling.

Table 2: Comparison of three methods for two typical months.

	May				September			
	Heuristic	VSA	LSA	HSA	Heuristic	VSA	LSA	HSA
Operating hours of installed capacity (h)								
Plant 1	475.2	484.8	499.2	499.2	264	288	288	288
Plant 2	499.2	499.2	499.2	499.2	304	284.8	284.8	288
Plant 3	475.2	499.2	499.2	499.2	244.8	278.4	292.8	288
Plant 4	499.2	499.2	499.2	499.2	268.8	282.2	282.2	288
Plant 5	489.6	499.2	499.2	499.2	288	288	288	288
Plant 6	499.2	499.2	499.2	499.2	288	288	288	288
Plant 7	499.2	499.2	499.2	499.2	288	288	288	288
Plant 8	489.6	499.2	499.2	499.2	288	288	288	288
Plant 9	480	480	480	499.2	268.8	288	288	288
Average (h)	489.6	495.5	497.1	499.2	278.04	285.9	287.5	288
Max-min difference (h)	24	19.2	19.2	0	59.2	9.6	10.6	0
Objective value (h2)	97.28	50.06	36.4	0	282.61	10.81	7.17	0

In a comparison of the results obtained by the HSA with those obtained by the heuristic, the VSA and the LSA are shown in Table 2. As indicated by the table, the results improve progressively in going from the heuristic to the HSA for most of the evaluation criteria, including the average, the max-min difference, and the objective value, for both May and September. It should be noted that the most improved solutions were achieved by the VSA, which demonstrated that the VSA has the capability to find the optimal solution. The LSA attempts to improve the objective function value and avoid convergence to a local minimum. As shown in Table 2, Plant 1 was changed in May by the LSA. Although the max-min difference remained the same, the objective function was diminished from 50.06 to 36.4. There is little difference in the results obtained between September and May. Due to the adjustments to the generating units in the valley periods by the LSA, the max-min difference was greater, but the objective function decreased from 10.81 to 7.17. Equal values for all three evaluation criteria were attained for May and September using the HSA, which indicates that the HSA has the capability to find the global minimum.

The generation requirements for the 9 plants in May are shown in Figure 5 and the details of results are listed in Table 3. Meanwhile, the generation requirements and details in September are shown in Figure 6 and Table 4. From Tables 3 and 4, it can be seen that the boot capacity result of each plant can meet all constraints. In Plant 2 in Table 3, for example, the days of first peak in plant output are 8 (from 7th to 14th) which is bigger than minimum duration of peak in plant output $T_k^{\text{peak,min}} = 7$ days, while the days of first valley in plant output are 4 (from 17th to 20th) which is bigger than minimum duration of valley in plant output $T_k^{\text{valley,min}} = 3$ days. Figure 5 shows that the outputs of most of the plants by the end of May were reduced to take advantage of the hydropower system. Plant 4 appears to have been an exception to this trend in May and could not satisfy the peak time constraint by the end of May, but this result is misleading. Table 1 shows that Plant 4 has two types of turbine units, 2 units of 200 MW capacity and 2 units of 300 MW capacity. As described in Section 3.1, Plant 4 was divided into two "virtual plants" for computational purposes. Table 3 and Figure 7 show the generation requirements for "virtual plants" 1 and 2 and demonstrate that these plants exhibit the same performance as the other plants. Conversely, the outputs of all of the plants increased from the beginning of September. Figures 5 and 6 demonstrate that the MTSFTPP results for May and September are reasonable.

Figures 8 and 9 show the generation and capacity requirements in May and September, respectively. It can be observed that the generation requirements are between maximum and minimum capacity.

5. Conclusions

A model for the MTSFTPP problem was proposed. The model includes three stages. The feasible spaces for the MTSFTPP problem are first produced by narrowing the search space based on constraints 1 and 2. Next, an initial feasible solution for the MTSFTPP problem is obtained using virtual plants and considering constraints 3 and 4. The POA is used to solve the MTSFTPP problem, and the optimal search is referred to as the VSA. To avoid convergence to a local minimum, the LSA is used, and the updated solution is used as a new feasible starting point for the next search with the VSA. Thus, the HSA is produced by combining the LSA with the VSA. A complete framework for solving the MTSFTPP problem was established and demonstrated using a case study. The results showed that the proposed method can efficiently produce satisfactory solutions with practical requirements.

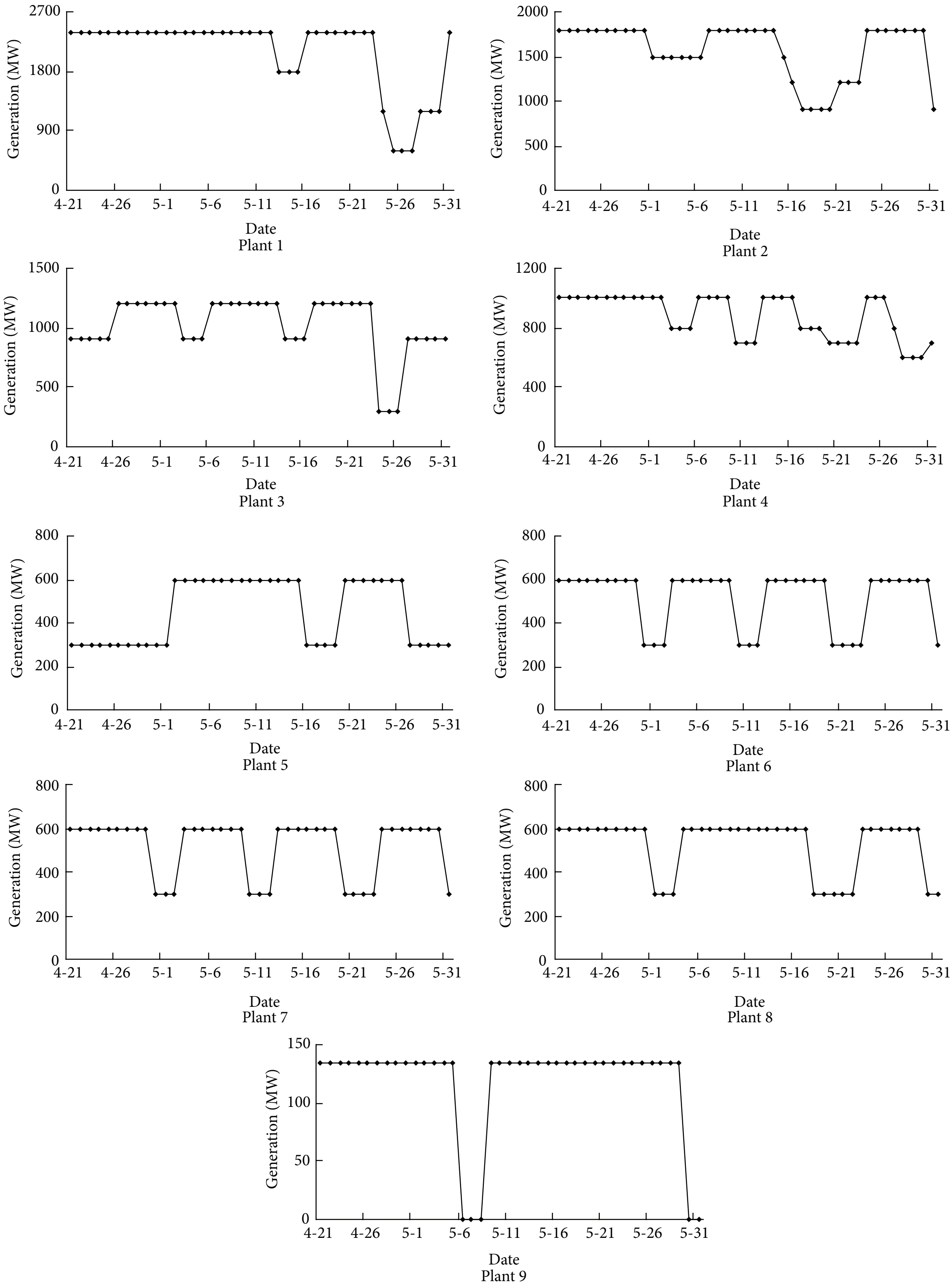

FIGURE 5: The process of generation requirements for Plants 1 to 9 in May.

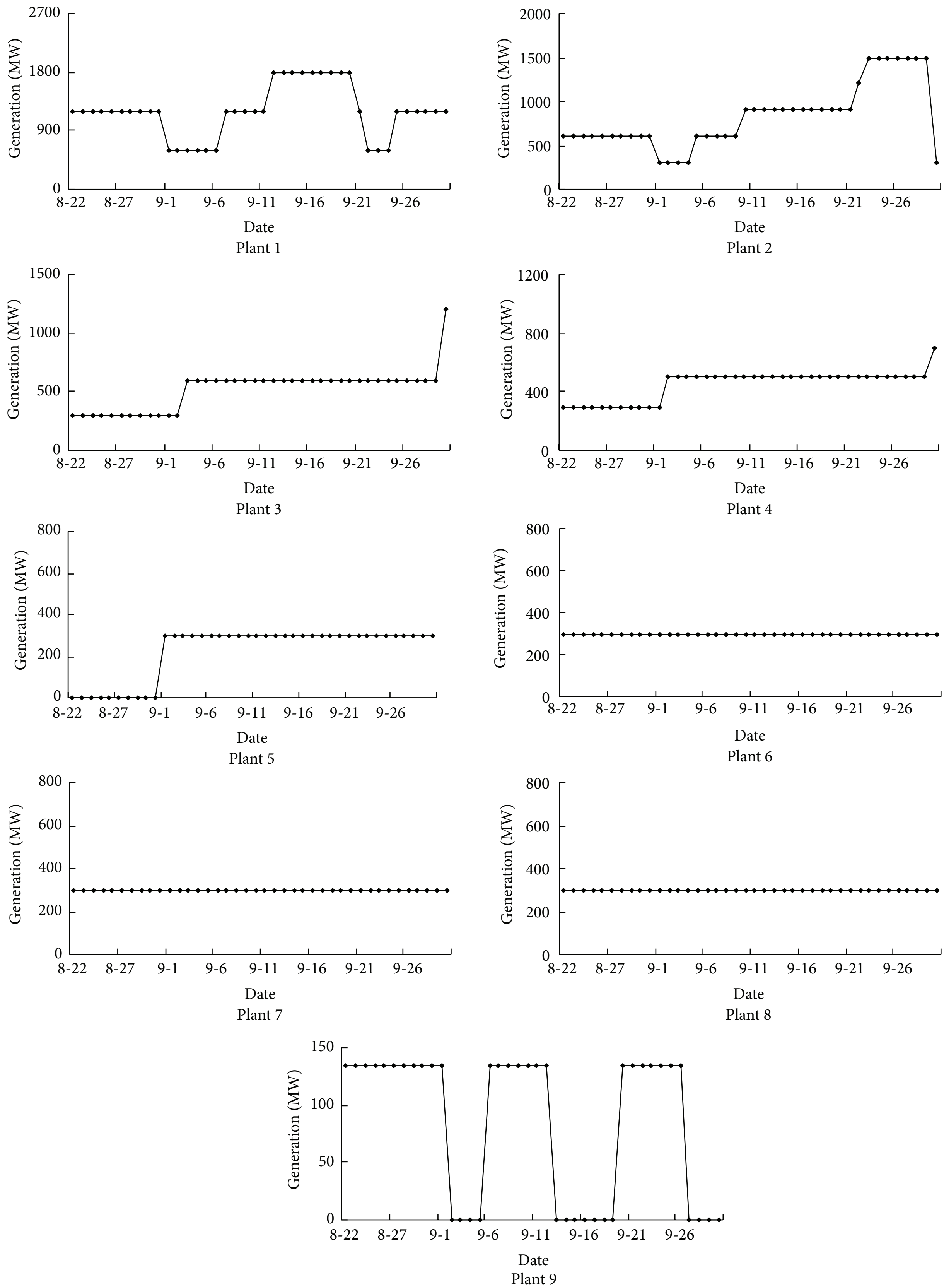

Figure 6: The process of generation requirements for Plants 1 to 9 in September.

Table 3: Results of generation requirements for Plants 1 to 9 in May (MW).

Date	Plant 1	Plant 2	Plant 3	Plant 4			Plant 5	Plant 6	Plant 7	Plant 8	Plant 9
				Virtual plant 1	Virtual plant 2	Total					
1st	2400	1500	1200	400	600	1000	300	300	300	300	135
2nd	2400	1500	1200	400	600	1000	600	300	300	300	135
3rd	2400	1500	900	200	600	800	600	600	600	300	135
4th	2400	1500	900	200	600	800	600	600	600	600	135
5th	2400	1500	900	200	600	800	600	600	600	600	135
6th	2400	1500	1200	400	600	1000	600	600	600	600	0
7th	2400	**1800**	1200	400	600	1000	600	600	600	600	0
8th	2400	**1800**	1200	400	600	1000	600	600	600	600	0
9th	2400	**1800**	1200	400	600	1000	600	600	600	600	135
10th	2400	**1800**	1200	400	300	700	600	300	300	600	135
11th	2400	**1800**	1200	400	300	700	600	300	300	600	135
12th	2400	**1800**	1200	400	300	700	600	300	300	600	135
13th	1800	**1800**	1200	400	600	1000	600	600	600	600	135
14th	1800	**1800**	900	400	600	1000	600	600	600	600	135
15th	1800	1500	900	400	600	1000	600	600	600	600	135
16th	2400	1200	900	400	600	1000	300	600	600	600	135
17th	2400	**900**	1200	200	600	800	300	600	600	600	135
18th	2400	**900**	1200	200	600	800	300	600	600	300	135
19th	2400	**900**	1200	200	600	800	300	600	600	300	135
20th	2400	**900**	1200	400	300	700	600	300	300	300	135
21st	2400	1200	1200	400	300	700	600	300	300	300	135
22nd	2400	1200	1200	400	300	700	600	300	300	300	135
23rd	2400	1200	1200	400	300	700	600	300	300	600	135
24th	1200	1800	300	400	600	1000	600	600	600	600	135
25th	600	1800	300	400	600	1000	600	600	600	600	135
26th	600	1800	300	400	600	1000	600	600	600	600	135
27th	600	1800	900	200	600	800	300	600	600	600	135
28th	1200	1800	900	0	600	600	300	600	600	600	135
29th	1200	1800	900	0	600	600	300	600	600	600	135
30th	1200	1800	900	0	600	600	300	600	600	300	0
31st	2400	900	900	400	300	700	300	300	300	300	0

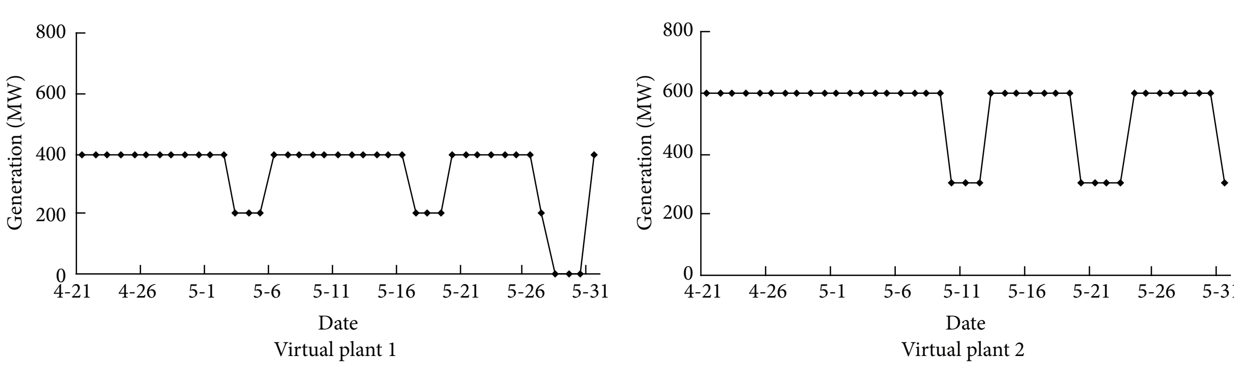

Figure 7: The process of generation requirements for “virtual plants” 1 and 2.

Table 4: Results of generation requirements for Plants 1 to 9 in September.

Date	Plant 1	Plant 2	Plant 3	Plant 4	Plant 5	Plant 6	Plant 7	Plant 8	Plant 9
1st	600	300	300	300	300	300	300	300	135
2nd	600	300	300	600	300	300	300	300	0
3rd	600	300	600	600	300	300	300	300	0
4th	600	300	600	600	300	300	300	300	0
5th	600	600	600	600	300	300	300	300	0
6th	600	600	600	600	300	300	300	300	135
7th	1200	600	600	600	300	300	300	300	135
8th	1200	600	600	600	300	300	300	300	135
9th	1200	600	600	600	300	300	300	300	135
10th	1200	900	600	600	300	300	300	300	135
11th	1200	900	600	600	300	300	300	300	135
12th	1800	900	600	600	300	300	300	300	135
13th	1800	900	600	600	300	300	300	300	0
14th	1800	900	600	600	300	300	300	300	0
15th	1800	900	600	600	300	300	300	300	0
16th	1800	900	600	600	300	300	300	300	0
17th	1800	900	600	600	300	300	300	300	0
18th	1800	900	600	600	300	300	300	300	0
19th	1800	900	600	600	300	300	300	300	0
20th	1800	900	600	600	300	300	300	300	135
21st	1200	900	600	600	300	300	300	300	135
22nd	600	1200	600	600	300	300	300	300	135
23rd	600	1500	600	600	300	300	300	300	135
24th	600	1500	600	600	300	300	300	300	135
25th	1200	1500	600	600	300	300	300	300	135
26th	1200	1500	600	600	300	300	300	300	135
27th	1200	1500	600	600	300	300	300	300	0
28th	1200	1500	600	600	300	300	300	300	0
29th	1200	1500	600	600	300	300	300	300	0
30th	1200	300	1200	900	300	300	300	300	0

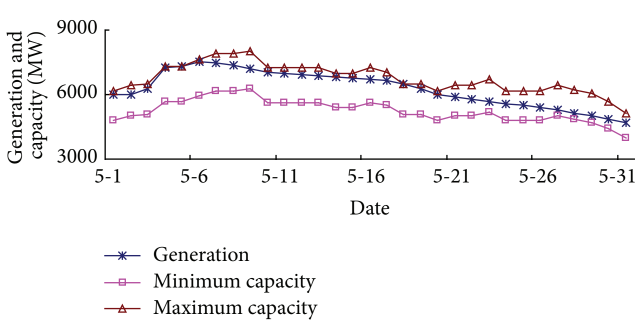

Figure 8: Generation and capacity requirements in May.

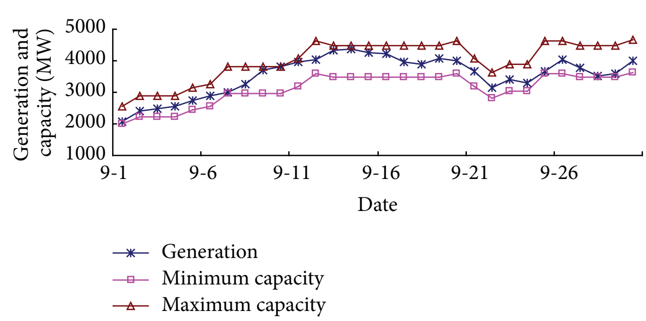

Figure 9: Generation and capacity requirements in September.

A novel method focusing on solving strategies for the MTSFTPP problem was proposed, in which the thermal system load was given after the other electric sources were optimized. However, the joint modeling of thermal power system with other source systems in midterm schedule can be considered as a research basis for future studies.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This study is supported by the Major International Joint Research Project (no. 51210014), the National Natural Science Foundation of China (no. 51209029), and the Fundamental Research Funds for the Central Universities (no. DUT14QY15).

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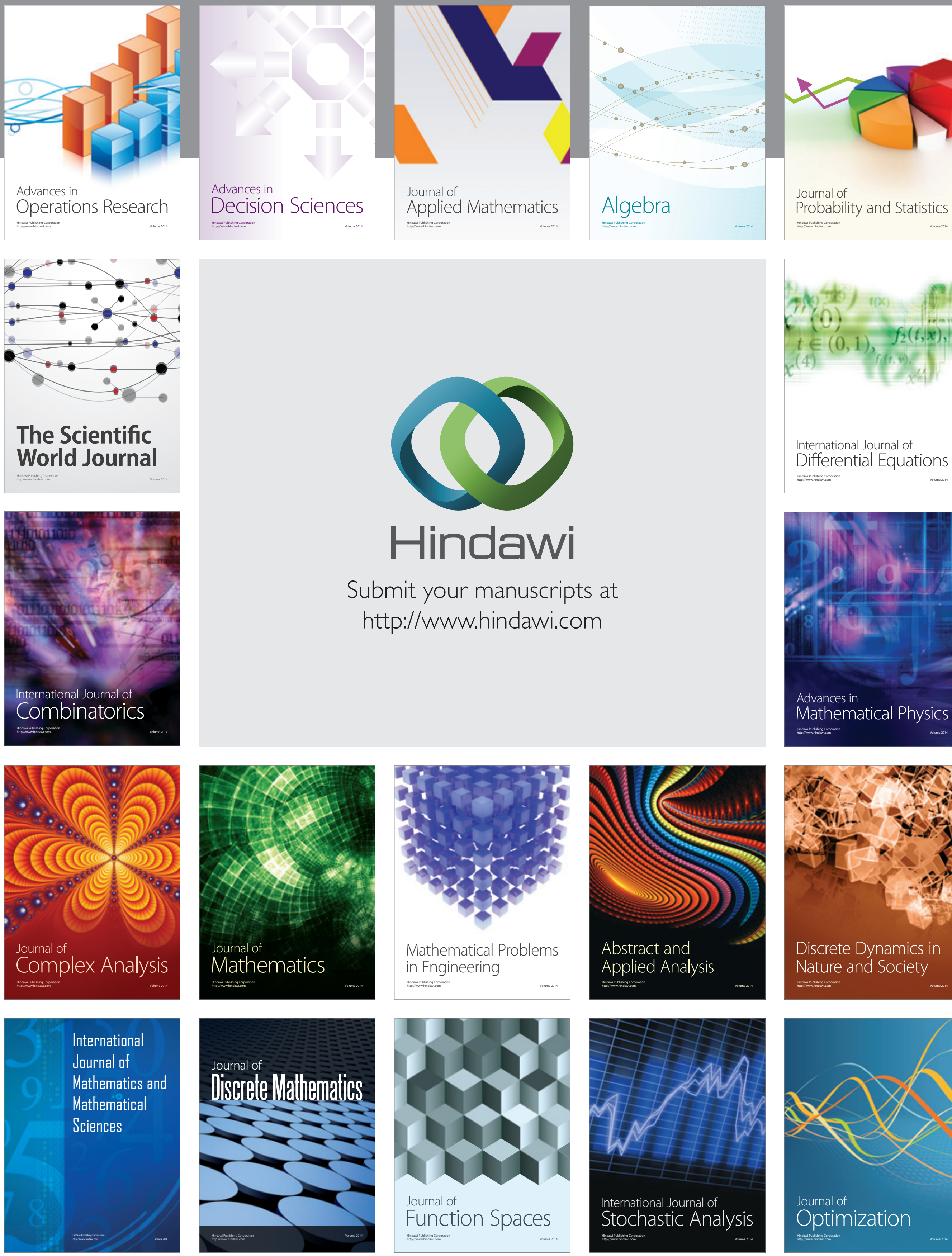
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