10

A Modified Fireworks Algorithm to Solve the Heat and Power Generation Scheduling Problem in Power System Studies

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10.1 Introduction

Combined Heat and Power (CHP) production has been introduced as a much more efficient scheme to generate power in plants and heat in boilers, offering higher energy efficiency and far lower fuel consumption [1]. Following the increasing growth of CHP units over the last decade, the conventional Economic Load Dispatch (ELD), which determined operating points of thermal plants in power-only production optimization problems, is transformed to Combined Heat and Power Scheduling (CHPS). Obviously, considering a primary objective function that is minimizing the operational cost, more constraints involved in the CHPS make it more difficult to solve compared to the ELD. As the most severe constraint to be satisfied, load balance including both power and heat can be pointed out. The authors in [2] have also considered the valve point effect in the CHPS problem that adds a sinusoidal term to the quadratic cost function of conventional thermal units. Although this modeling presents a more realistic viewpoint, it increases the nonlinearity order of the problem. To include transmission losses in the CHPS problem, two different ways can be followed. The first and the most accurate one is to model transmission lines and other network details such as bus voltages in the context of Power Flow (PF) or Optimal Power Flow (OPF) [3].

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However, as the second solution, some attempts have been made to include transmission losses using Kron's loss formula – an equivalent loss matrix – into the CHPS without considering the voltage of the network busses [4, 5]. Another consideration that turns the CHPS problem into a complex optimization problem is the issue of Feasible Operating Region (FOR) owning to CHP units. Different types of CHP units have different FORs determined by CHP units' manufacturer. In reality, these FORs are non-convex [6–11]. However, in some studies, they have been approximated by convex ones with the aim of simplicity [12, 13].

Before moving on to the further operational step, it is worth mentioning that ELD presents an optimal operating point associated with only one snapshot of the power system, while System Operators (SOs) need a wider time resolution for the operational goals and this is where the Short-term CHPS arises. The CHPS is mainly discussed over the 24 hours, or 168 hours, that is daily or weekly and determines the optimal operating points of each generating unit in order to minimize the operating cost. Needless to say, considering CHP units in the short-term scheduling problem is of high importance for SOs. In this respect, the authors in [14–16] have presented CHP Unit Commitment (CHPUC) models in which minimum up/down time limitations of units are taken into consideration. Anand et al. in [14] have considered the flexibility of CHP units taking advantage of replacing single-shaft turbines with multi-shaft ones to provide a variable ratio of heat and power output, called dual-mode CHP. To investigate the daily generation scheduling of CHP in various viewpoints and with different considerations, plenty of research has been carried out [13, 17–22]. PF constraints have been included in [17] while the model proposed in [18] has been further elaborated to include security constraints of the power system. Furthermore, the inclusion of Electric Storage System (ESS), Thermal Storage System (TSS), and industrial customers have been taken into account in the CHPS problem [13, 20]. Minimizing the toxic emissions such as CO_2 is the subsidiary goals in the CHPS. In this regard, an optimal model desirable for Generation Companies (GENCOs) has been proposed in the [21] to minimize the cost associated with both operational and environmental CO_2 emissions. To present an accurate model, the valve-point effect of thermal units and spinning reserve market has also been seen in [21]. In [22], short-term participation of CHP units is investigated in the presence of demand response programs while a heat buffer tank is incorporated into the framework to store heat. Over a wider time span, Majić et al. in [19] studied a 48-hour CHP scheduling considering energy storage, while most of the aforementioned studies in the literature have carried out day-ahead scheduling.

Achieving optimal solutions in the CHPS problem has always been a challenging and attractive issue for power SOs and researchers. In between, evolutionary algorithms have always played a pivotal role in reaching optimal solutions. Similar to many other engineering optimization problems, basic Genetic Algorithm (GA) or some modified versions are the most favorable tools for the proposed problem. The Improved Genetic Algorithm with Multiple Updating (IGA-MU) is used to solve the CHPS problem in [6]. The IGA-MU takes advantage of the Improved Evolutionary Direction Operator (IEDO), which effectively searches for solutions and a Multiplier Updating (MU) tool to avoid deforming the augmented Lagrange function. The authors in [10] have employed a Self-Adaptive Real-Coded GA (SARGA) for the CHPS, by which the exploration capability of the basic GA is considerably improved. In this technique, a selection tournament is created using a Simulated Binary Crossover (SBX) between two solutions and eventually the better one is considered to be placed in a mating pool. GA can also act as a part of a heuristic approach in the CHPS problem. In [21], the proposed model is divided into two loops, one loop for thermal units and the one for demand, and the former is handled by GA. Particle swarm optimization (PSO) is another powerful tool to cope with the problem of CHPS. Indeed, PSO with selective operators was conducted on the CHPS problem [11] when it was, later on, revealed that the results might be either infeasible or trapped into local optimums. To overcome this shortage, Time-Varying Acceleration Coefficients PSO (TVAC-PSO) is proposed and has been tested on the CHPS problem [5]. Indeed, TVAC-PSO benefits from the adaptive coefficients in the PSO that can vary during iterations. Moreover, a heuristic PSO-based optimization, called Civilized Swarm Optimization (CSO), has been used to solve daily scheduling of CHP units in [14]. In this algorithm, the local search is done by means of binary successive approximation which iteratively updates the unit status. Apart from GA and PSO, other evolutionary algorithms have found their paths to CHP generation scheduling. Vasebi et al. in [7] applied Harmony Search Algorithm (HSA) to the CHPS problem. However, the solutions were infeasible in some cases. It is worth mentioning that an analogy made in [23] between HSA and Lagrangian Relaxation (LR) method demonstrated the effectiveness of the HSA in large-scale networks. [9] showed that the Ant Colony Search Algorithm (ACSA) itself has some difficulties in terms of CHPS constraints handling and convergence, and therefore attempted to bridge the gap with the help of Tuba Search (TS) and GA incorporated into the ACSA. To reduce the computational burden of the CHPS problem, the authors in [24] utilized the Bee Colony Optimization Algorithm (BCOA) while its performance was validated by comparing the obtained results with those of Real Coded Genetic Algorithm (RCGA) and PSO. Also, Rong et al. in [16] has introduced a new dynamic programing approach for the CHPUC named Dynamic Regrouping-based Dynamic Programing-Relaxation and Sequential Commitment (DRDP-RSC) which investigates the generation scheduling of CHP on a daily, weekly, and monthly basis. To see more applications of heuristic and evolutionary algorithms in solving Combined Heat and Economic Dispatch (CHPED), a comprehensive review has been carried out in [25].

10.1.1 Statistics Related to Documents

This section reports statistics related to the published documents in the field of ELD and Combined Heat and Power Scheduling (CHPS) using the Scopus database. The search resulted in 274 documents.

Figure 10.1 shows the number of documents published each year from 1990 and Figure 10.2 depicts the journals with the highest number of publications in the area of CHPS, where *Energy* is the most interesting journal. The authors and

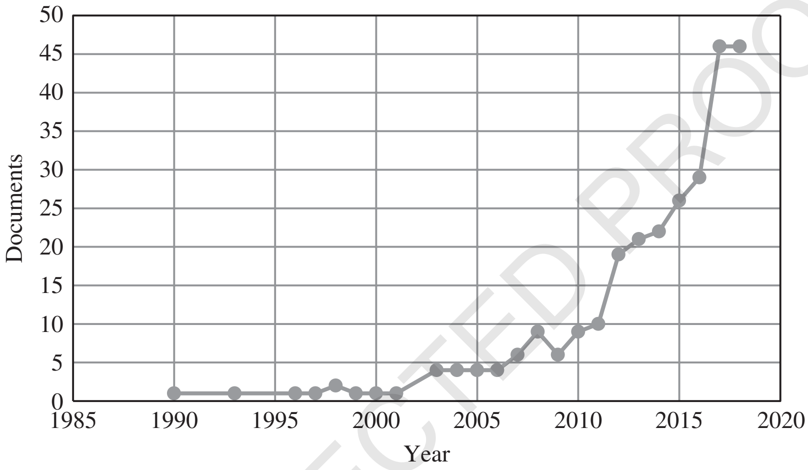

Figure 10.1 Documents by year.

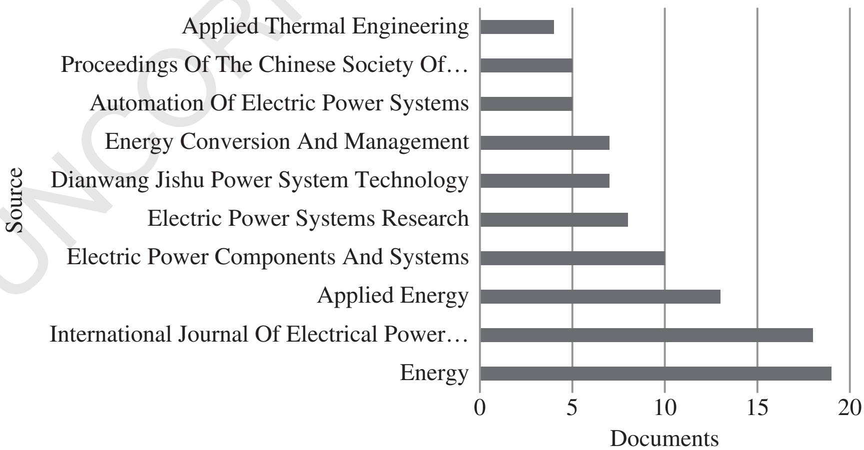

Figure 10.2 Documents by source.

the universities with the highest number of publications in the area of CHPS have been sorted in Figures 10.3 and 10.4 where M. Basu and his affiliated university, Jadavpur University, have been ranked first.

Figure 10.1 depicts the number of publications per year.

Figure 10.2 depicts the number of publications by source and Figure 10.3 depicts the number of publications by author.

Besides, Figure 10.4 depicts the number of publications by affiliation and Figure 10.5 indicates the number of publications by country.

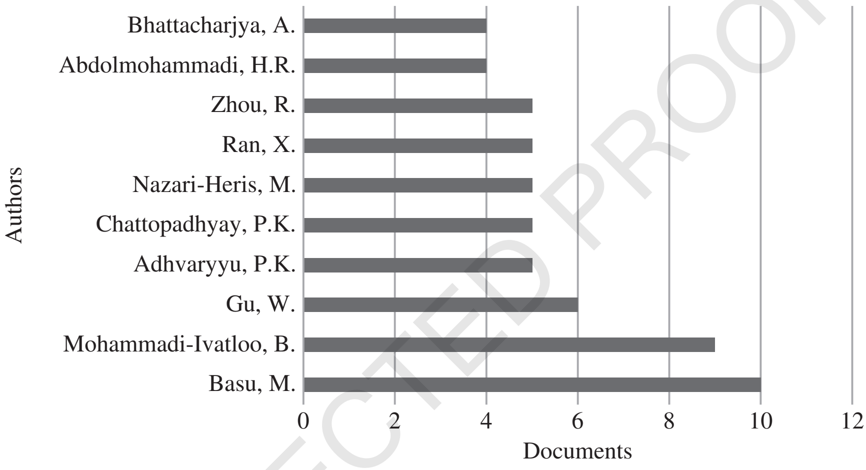

Figure 10.3 Documents by author.

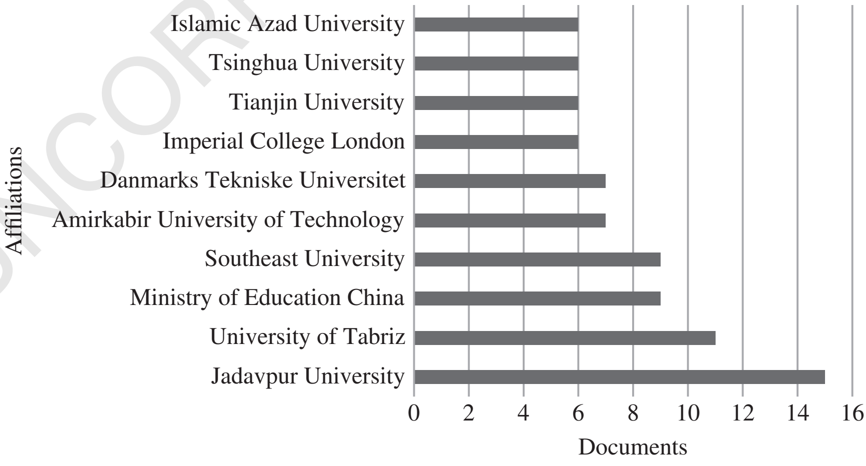

Figure 10.4 Documents by affiliation.

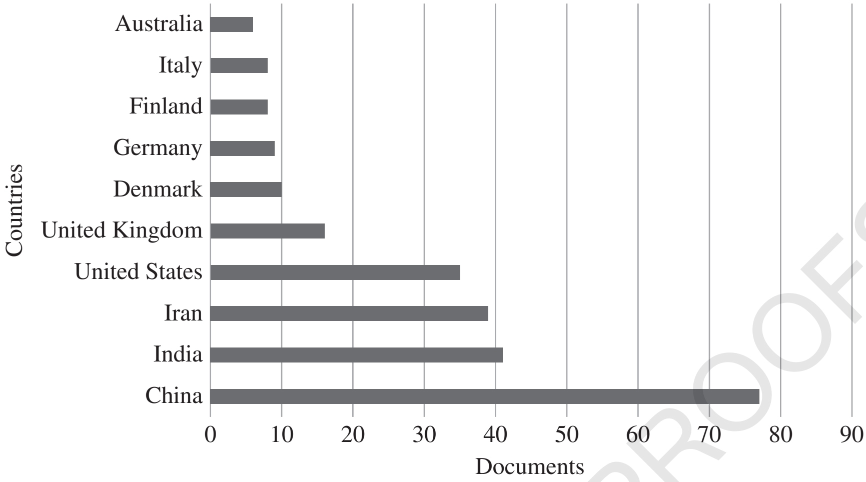

Figure 10.5 Documents by country.

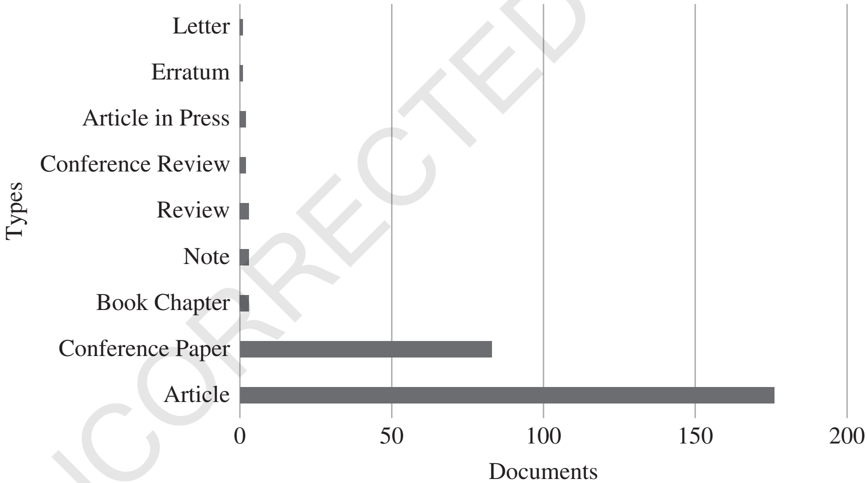

Figure 10.6 Documents by type.

Figure 10.6 illustrates the numbers of publications by type while Figure 10.7 shows the number of publications by subject area.

In this study, the problem of short-term CHPS is investigated using the modified fireworks algorithm [26] as an optimization tool. The modified fireworks algorithm is one of the emerging heuristic population-based algorithms that show a strong performance in complex optimization problems. Moreover, the proposed problem is simulated in two phases, which are ELD and CHPS. In the first phase,

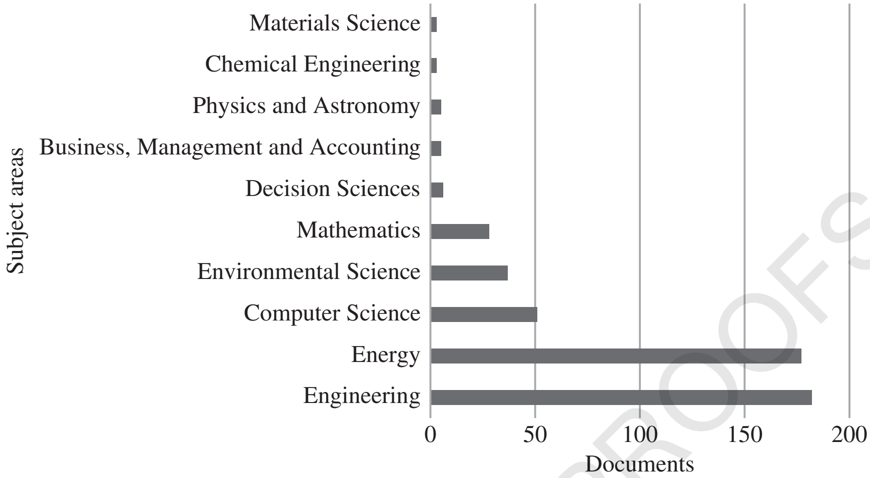

Figure 10.7 Documents by subject area.

aiming at demonstrating the effectiveness of the modified fireworks algorithm in terms of optimality and feasibility, the obtained results are compared with those of existing evolutionary algorithms. In the second stage, the daily CHP scheduling is studied. The results illustrate that the modified fireworks algorithm is well capable of handling the proposed problem and guaranteeing the optimal solution.

The remaining sections are structured as follows. Section 10.2 formulates the objective function and constraints of the problem while Section 10.3 explains the modified fireworks algorithm. Section 10.4 is devoted to the numerical simulations and, finally, Section 10.5 draws some conclusions.

10.2 Modeling

The CHPS problem is a non-linear optimization problem, mainly due to the fuel cost function of the generating units. First, the simpler form of the CHPS problem is proposed in the context of CHPED problem, where the scheduling period is one hour. It is worth mentioning that the CHPS problem is defined for more than one hour and usually up to 168 hours on an hourly basis. The basic economic dispatch problems are only proposed to determine the operating points of the thermal generating units, while it has been more completed by taking into consideration the valve-point effect and the transmission system losses. The CHPS problem has been introduced to power system studies in recent years, and different solution methods have been used so far. The CHPED problem is proposed to determine the optimal operating point of those units in service such that the electrical and heat load demand is fully met. This problem is generally formulated as an optimization problem with the cost function to be minimized as:

$$Min \quad TC = \sum_{i=1}^{N_T} F_i^T\left(PG_i^T\right) + \sum_{j=1}^{N_B} F_j^B\left(PH_j^B\right) + \sum_{k=1}^{N_{CHP}} F_k^{CHP}\left(PG_k^{CHP}, PH_k^{CHP}\right) \tag{10.1}$$

In the objective function, TC stands for the total cost, which includes the fuel cost of thermal generating units denoted by $F_{j,t}^B\left(PH_{j,t}^B\right)$, the fuel cost of heat-only units denoted by $F_{j,t}^B\left(PH_{j,t}^B\right)$, as well as the fuel cost of CHP units indicated by $F_{k,t}^{CHP}\left(PG_{k,t}^{CHP}, PH_{k,t}^{CHP}\right)$, as respectively presented in Eqs. (10.2)–(10.4).

$$F_i^T\left(PG_i^T\right) = \alpha_i\left(PG_i^T\right)^2 + \beta_i PG_i^T + \gamma_i + \left|\lambda_i \sin\left(\rho_i\left(PG_i^{T,Min} - PG_i^T\right)\right)\right| \tag{10.2}$$

$$F_j^B\left(PH_j^B\right) = a_j\left(PH_j^B\right)^2 + b_j PH_j^B + c_j \tag{10.3}$$

$$F_k^{CHP}\left(PG_k^{CHP}, PH_k^{CHP}\right) = a_k\left(PG_k^{CHP}\right)^2 + b_k PG_k^{CHP} + c_k + d_k\left(PH_k^{CHP}\right)^2 + e_k PH_k^{CHP} + f_k PG_k^{CHP} PH_k^{CHP} \tag{10.4}$$

The expression presented for modeling the fuel cost of thermal generating units includes a sinusoidal term added to a polynomial function as shown in Figure 10.8. In this regard, the conventional cost function of thermal generating units is modeled using a polynomial function of the second order while assigning the impact of the valve-point effect causes a sinusoidal effect, shown by the second term. The fuel cost function of the heat-only units has been represented in Eq. (10.3) while Eq. (10.4) represents the cost function of CHP units. It is noteworthy that the problem presented includes several constraints.

$$\sum_{j=1}^{N_B} PH_j^B + \sum_{k=1}^{N_{CHP}} PH_k^{CHP} = PH_L \tag{10.5}$$

$$\sum_{i=1}^{N_T} PG_i^T + \sum_{k=1}^{N_{CHP}} PG_k^{CHP} = PG_L \tag{10.6}$$

$$PG_i^{T,Min} \le PG_i^T \le PG_i^{T,Max} \tag{10.7}$$

$$PH_j^{B,Min} \le PH_j^B \le PH_j^{B,Max} \tag{10.8}$$

$$\left\{PG_k^{CHP}, PH_k^{CHP}\right\} \in FOR_k^{CHP} \tag{10.9}$$

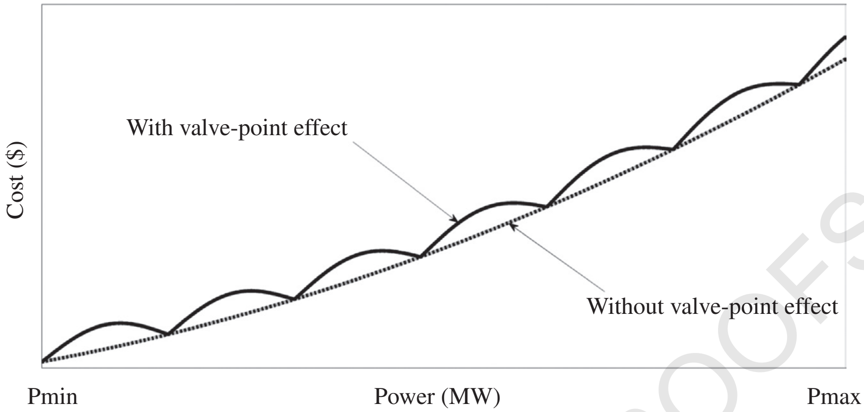

Figure 10.8 The fuel cost function of thermal generating units.

The power and heat balance equations are regarded as the most significant limitations in power systems so that the generated heat and electrical power should be exactly equal to the heat and electrical load demands as Eqs. (10.5) and (10.6), respectively. The power generation limits of thermal, heat-only, and CHP units are indicated through Eqs. (10.7)–(10.9), respectively. As shown in Eq. (10.9), the CHP should operate in the permitted range, which is a 2D closed surface characterized by the generated heat and power known as Feasible Operating Region (FOR). This chapter takes into account three types of FORs as demonstrated in Figures 10.9–10.11.

The FOR of the CHP units can be either convex known as "Type 1" or non-convex known as "Type 2" or "Type 3." Generally, specifying the optimal operating point within Type 2 and Type 3 FORs would be a difficult task which may be intractable on several occasions. Stepping up the generated electrical power in Type 1 CHPs causes the generated heat to reduce. Stepping up the generated heat also leads to electrical power reduction. Such circumstances are regarded as common operation of CHP units. As Figure 10.9 shows, the angles of Type 1 FOR are all less than 180°, while this is not true for Type 2 and Type 3 CHPs, as Figures 10.10 and 10.11 indicate.

10.2.1 Modeling Using a Heuristic Approach

Using heuristic methods for solving the presented method, the objective function and the constraints should be stated properly. First, the variables of the problem should be specified. For the ELD problem in which the operating point of all assets should be determined, one variable should be defined for each of the heat-only units, one variable for each thermal unit, and two variables for each CHP

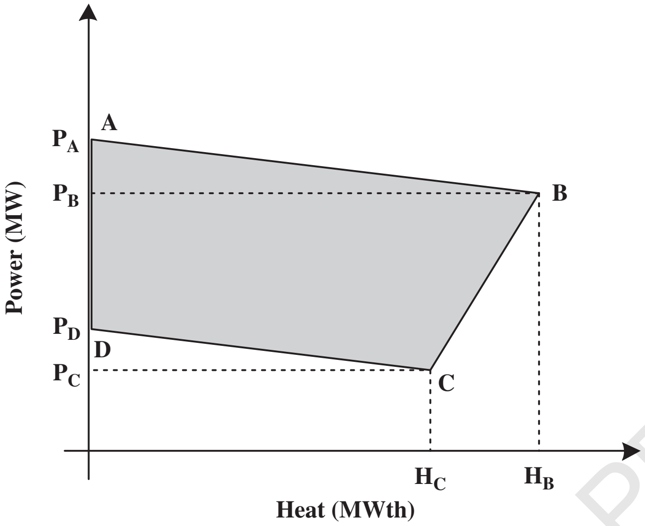

Figure 10.9 Convex FOR (Type: 1) [5] (*Source:* Electric Power Systems Research Journal with permission from Elsevier).

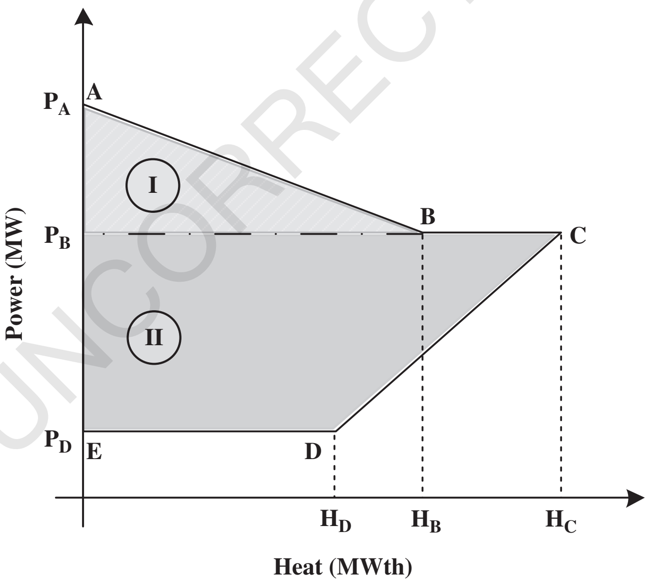

Figure 10.10 Non-convex FOR (Type: 2) [5] (*Source:* Electric Power Systems Research Journal with permission from Elsevier).

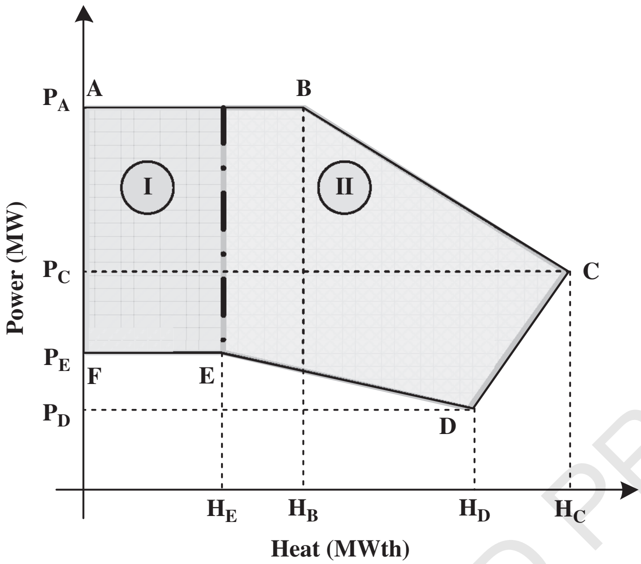

Figure 10.11 Non-convex FOR (Type: 3) [5] (*Source:* Electric Power Systems Research Journal with permission from Elsevier).

unit. It should be noted that these operating points must be within the FOR of the CHP unit. In this respect, N_T, N_B, and N_{CHP} variable matrices should be defined as follows proportionally to the number of thermal units, heat-only units, and CHP units, respectively:

$$Var = \left[\underbrace{pg_2^T, \ldots, pg_{N_T}^T}_{Thermal\ Units-1}; \underbrace{ph_2^B, \ldots, ph_{N_B}^T}_{Boilers-1}; \underbrace{pg_1^{CHP}, \ldots, pg_{N_{CHP}}^{CHP}; ph_1^{CHP}, \ldots, ph_{N_{CHP}}^{CHP}}_{CHP\ Units} \right] \tag{10.10}$$

In general, optimization problems constrained by lower and upper limits on a single variable can be modeled using a simple mapping of the stochastic space [0,1] to the permitted range. For instance, the power generation of thermal units and heat generation of heat-only units are stated as follows:

The one-dimensional mapping is used to determine the permitted operating range of the thermal and heat-only units as stated in Eqs. (10.11)–(10.12).

$$PG_i^T = PG_i^{T,Min} + pg_i^T \left(PG_i^{T,Max} - PG_i^{T,Min} \right) \tag{10.11}$$

$$PH_j^B = PH_j^{B,Min} + ph_j^B \left(PH_j^{B,Max} - PH_j^{B,Min} \right) \tag{10.12}$$

The two-dimensional mapping should be used for the CHP units as the electricity and heat generation are mutually related. In this respect, the relationship between the FOR and the stochastic variables should be optimally implemented. For instance, for the convex FOR shown in Figure 10.9, it can be easily modeled. The mapped two-dimensional FOR, which is a rectangle, is depicted in Figure 10.12.

Accordingly, the primary mapping is obtained as follows:

$$PG_k^{CHP} = PG_k^{CHP,Min} + pg_k^{CHP}\left(PG_k^{CHP,Max} - PG_k^{CHP,Min}\right) \tag{10.13}$$

$$PH_k^{CHP} = PH_k^{CHP,Min} + ph_k^{CHP}\left(PH_k^{CHP,Max} - PH_k^{CHP,Min}\right) \tag{10.14}$$

After the two-dimensional mapping, it is necessary to apply the CHP-related constraints. If the heat generation is between 0 and H_C, the generated power must be within the area surrounded by the line connecting points $(0,P_A)$ and (H_B,P_B) and the line connecting points $(0,P_D)$ and (H_C,P_C). For example, if the electricity generation is above the first line or below the second line, the electric power generation must be fixed on the corresponding value on the mentioned lines. For the state in which the heat generation is between Hc and H_B, the electrical power generation must within the area surrounded by the line connecting points (H_B,P_B) and (H_C,P_C) and line connecting points $(0,P_A)$ and (H_B,P_B). If the electrical power generation is outside this area, the value of electrical power generation must be fixed on the line.

If the FOR is non-convex, using the above linear equations would make a part of the search space unreachable. This issue has been depicted in Figure 10.13.

In this regard, one solution would be dividing the search space into multiple convex sets. If one of the vertices of the FOR is greater than 180°, the plane

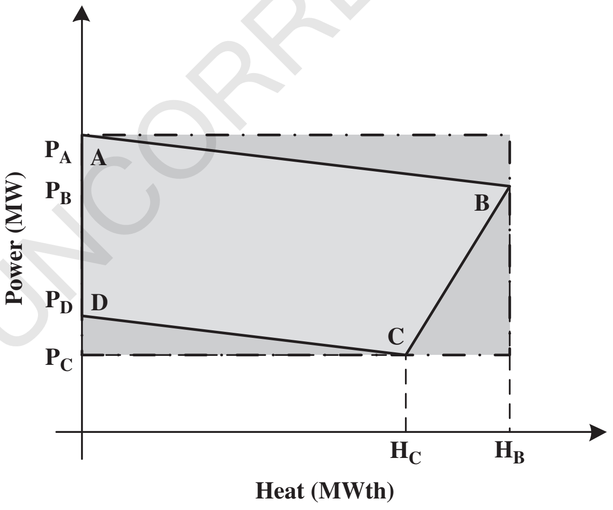

Figure 10.12 Two-dimensional mapping of the convex FOR.

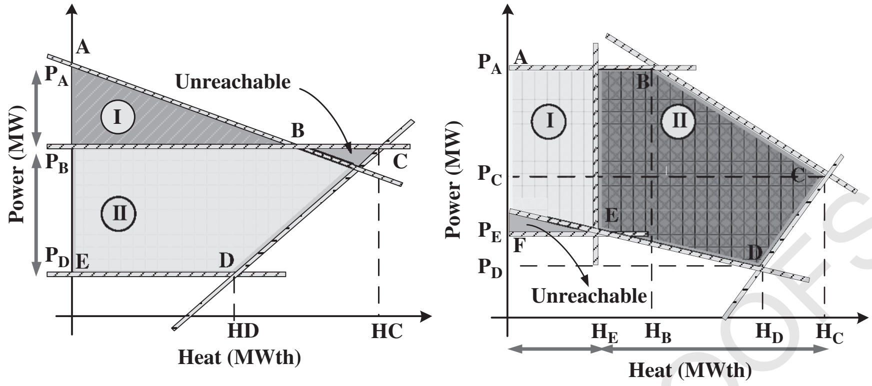

Figure 10.13 Unreachable areas in non-convex FORs.

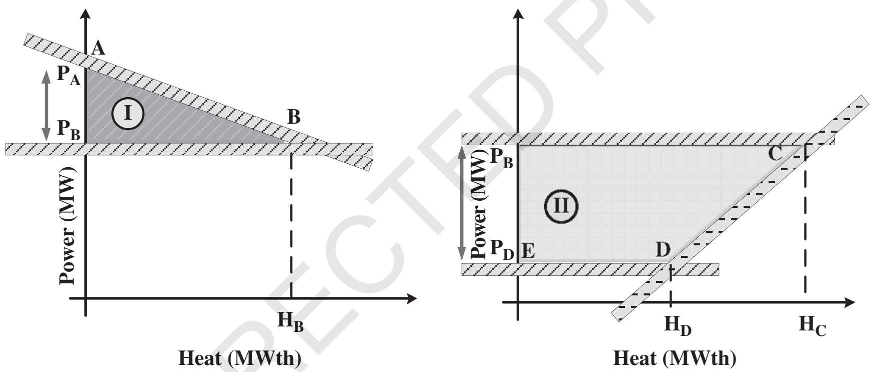

Figure 10.14 Decomposition technique for the Type 2 FOR.

mentioned would be non-convex. Thus the plane should be decomposed to several planes with all vertices less than 180°. Accordingly, the continuous problem will be converted into a discrete optimization problem. Using the above-mentioned technique, the linear equations proposed for the convex FOR can be used for each of the decomposed planes.

For the units with non-convex FOR, first the FOR is decomposed into two convex regions. Afterwards, using the technique mentioned, the operating points are determined. Figures 10.14 and 10.15 illustrate the decomposition technique used for non-convex FORs.

For the Type 2 FOR, in Figure 10.14, if the electrical power generation is between A and B, the equations corresponding to the region I are used. If the electrical power generation is between B and D, the equations corresponding to region 2 are used. In Figure 10.15 the regions would be selected after determining the heat power

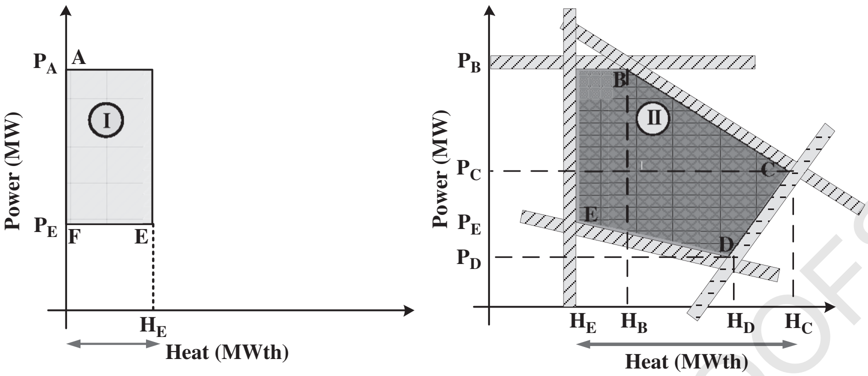

Figure 10.15 Decomposition technique for the Type 3 FOR.

generation. If the heat power is less than H_E, the equations corresponding to the region I are used. If the heat power generation is more than H_E, the equations corresponding to region II are used. After determining the power generation of the CHP units, other constraints of the units are applied. The most important constraint is the electrical and heat power balance equations. As mentioned in Eq. (10.10), the number of thermal units and heat-only units are N_T-*1* and N_B-*1*, respectively. It is noteworthy that the thermal unit 1 and the heat-only unit 1 are considered as the slack units. These units are supposed to ensure the electrical and heat power balance. As a result, the power balance constraint can be simply satisfied. However, it is possible that the power generation in slack units may be out of the feasible range of such units. If so, it should be assigned to the objective function using a penalty factor. The power generation equations of the slack thermal and heat-only units are stated as follows:

$$PG_1^T = PG_L - \sum_{i=2}^{N_T} PG_i^T - \sum_{k=1}^{N_{CHP}} PG_k^{CHP} \tag{10.15}$$

$$PH_j^B = PH_L - \sum_{j=2}^{N_B} PH_j^B - \sum_{k=1}^{N_{CHP}} PH_k^{CHP} \tag{10.16}$$

Finally, the objective function of the problem is reformulated as follows:

$$\begin{aligned} &Min \\ &TC = \sum_{i=1}^{N_T} F_i^T\left(PG_i^T\right) + \sum_{j=1}^{N_B} F_j^B\left(PH_j^B\right) + \sum_{k=1}^{N_{CHP}} F_k^{CHP}\left(PG_k^{CHP}, PH_k^{CHP}\right) \\ &\quad + \lambda_1^T\left\langle PG_1^T - PG_1^{T,Min}\right\rangle + \left\langle \lambda_1^T PG_1^{T,Max} - PG_1^T\right\rangle \\ &\quad + \lambda_1^B\left\langle PH_1^B - PH_1^{B,Min}\right\rangle + \left\langle \lambda_1^B PH_1^{B,Max} - PH_1^B\right\rangle \end{aligned} \tag{10.17}$$

The bracket-operator <> denotes the absolute value of the operand if the operand is negative; and if the operand is non-negative, it returns zero [5].

The simulation results obtained from mathematical and heuristic methods show that in cases where the problem and the FOR constraint has not been properly modeled, the operating points may fall out of the FORs. Moreover, reaching the global optimum would be very difficult due to the non-linear behavior of the problem. A section is presented in the simulation results to address this issue.

10.2.2 Expanding the ELD Problem to the Generation Scheduling Problem

As the chapter focuses on solving the CHPS problem, the ELD problem has been extended to the generation scheduling problem. Hence, the scheduling horizon will be more than one hour. The generation scheduling problem is generally defined over 24 hours, i.e. 1 day, or 168 hours, i.e. 1 week. Due to the fluctuating load demand over different hours, optimal operating points of the units would change from one hour to another. It is noteworthy that this change in the power and heat generation is limited due to technical and thermodynamic constraints. Such limitations should therefore be applied to the problem. The objective function and the constraints of the CHPS problem are presented as follows:

$$Min$$

$$TC = \sum_{t=1}^{N_H}\sum_{i=1}^{N_T} F_{i,t}^{T}\left(PG_{i,t}^{T}\right) + \sum_{t=1}^{N_H}\sum_{j=1}^{N_B} F_{j,t}^{B}\left(PH_{j,t}^{B}\right) + \sum_{t=1}^{N_H}\sum_{k=1}^{N_{CHP}} F_{k,t}^{CHP}\left(PG_{k,t}^{CHP}, PH_{k,t}^{CHP}\right) \tag{10.18}$$

$$F_{i,t}^{T}\left(PG_{i,t}^{T}\right) = \alpha_i\left(PG_{i,t}^{T}\right)^2 + \beta_i PG_{i,t}^{T} + \gamma_i + \left|\lambda_i \sin\left(\rho_i\left(PG_i^{T,Min} - PG_{i,t}^{T}\right)\right)\right| \tag{10.19}$$

$$F_{j,t}^{B}\left(PH_{j,t}^{B}\right) = a_j\left(PH_{j,t}^{B}\right)^2 + b_j PH_{j,t}^{B} + c_j \tag{10.20}$$

$$F_{k,t}^{CHP}\left(PG_{k,t}^{CHP}, PH_{k,t}^{CHP}\right) = a_k\left(PG_{k,t}^{CHP}\right)^2 + b_k PG_{k,t}^{CHP} + c_k + d_k\left(PH_{k,t}^{CHP}\right)^2 + e_k PH_{k,t}^{CHP} + f_k PG_{k,t}^{CHP} PH_{k,t}^{CHP} \tag{10.21}$$

$$\sum_{j=1}^{N_B} PH_{j,t}^{B} + \sum_{k=1}^{N_{CHP}} PH_{k,t}^{CHP} = PH_{L,t} \tag{10.22}$$

$$\sum_{i=1}^{N_T} PG_{i,t}^{T} + \sum_{k=1}^{N_{CHP}} PG_{k,t}^{CHP} = PG_{L,t} \tag{10.23}$$

$$PG_i^{T,Min} \le PG_{i,t}^T \le PG_i^{T,Max} \quad (10.24)$$

$$PH_j^{B,Min} \le PH_{j,t}^B \le PH_j^{B,Max} \quad (10.25)$$

$$\left\{PG_{k,t}^{CHP}, PH_{k,t}^{CHP}\right\} \in FOR_k^{CHP} \quad (10.26)$$

$$PG_{i,t}^T - PG_{i,t-1}^T \le RUPG_i^T \quad (10.27)$$

$$PG_{i,t-1}^T - PG_{i,t}^T \le RDPG_i^T \quad (10.28)$$

$$PH_{j,t}^B - PH_{j,t-1}^B \le RUPH_j^B \quad (10.29)$$

$$PH_{j,t-1}^B - PH_{j,t}^B \le RDPH_j^B \quad (10.30)$$

$$PG_{k,t}^{CHP} - PG_{k,t-1}^{CHP} \le RUPG_k^{CHP} \quad (10.31)$$

$$PG_{k,t-1}^{CHP} - PG_{k,t}^{CHP} \le RDPG_k^{CHP} \quad (10.32)$$

$$PH_{k,t}^{CHP} - PH_{k,t-1}^{CHP} \le RUPH_k^{CHP} \quad (10.33)$$

$$PH_{k,t-1}^{CHP} - PH_{k,t}^{CHP} \le RDPH_k^{CHP} \quad (10.34)$$

The objective function of the scheduling problem is defined as mitigating the total operating cost of the system while satisfying the electrical and heat load demand. The scheduling period of the problem is N_H hours while t is the index of time (one hour). In other words, the optimal operating points of the units are determined on an hourly basis. In addition to the constraints defined for the ELD problem, there are also other constraints that should be taken into consideration relating to the thermodynamic considerations of the units. One of these constraints is the ramping rate of the generating units which is defined as the maximum amount of power generation that can change from one hour to another. In this respect, the Ramp-Up (RU) and Ramp-Down (RD) limits have been considered for the units. The constraints of the scheduling problem which are in common with the ELD problem are modeled similarly, but the preliminary population matrix should be extended to the scheduling period, i.e. NH. Besides, the following framework is used to apply the RU and RD constraints. Assume that the power generation limitation is as follows:

$$P_x^{Min} \le P_{x,t} \le P_x^{Max} \quad (10.35)$$

This constraint is modeled as below for hour 2 to hour 24:

$$P_{x,t} = \hat{P}_{x,t}^{Min} + p_{x,t}\left(\hat{P}_{x,t}^{Max} - \hat{P}_{x,t}^{Min}\right) \qquad t > 1 \quad (10.36)$$

where the upper and lower bounds vary on an hourly basis. These bounds are stated as follows:

$$\hat{P}_{x,t}^{Min} = Max\left\{P_x^{Min}, P_{x,t-1} - RDP_x\right\} \tag{10.37}$$

$$\hat{P}_{x,t}^{Max} = Min\left\{P_x^{Max}, P_{x,t-1} + RUP_x\right\} \tag{10.38}$$

These bounds also depend upon the power generation of the units at the previous hour. Accordingly, the RU and RD constraints can be easily modeled. It should be noted that power generation at the first hour can be determined randomly using the preliminary matrix or using the power generation for the previous hour.

In the next section the proposed model is implemented on the ELD problem using the modified fireworks algorithm, and the results are verified. Moreover, some comparisons have been made with other references. Afterwards, the CHPS problem is simulated and the obtained results are discussed.

As mentioned in the ELD problem, determining the optimal operating point of the CHP unit is much more difficult compared to thermal and heat-only units. However, utilizing the suggested technique, the operating points can be optimally and simply determined.

10.3 Fireworks Algorithm

Fireworks optimization method was first introduced in 2010 for dealing with global optimization problems [27]. This algorithm comprises three main parts similar to other optimization algorithms as (i) initialization, (ii) local search and (iii) selection.

10.3.1 Initialization

The first step is to randomly choose N solutions from the search space as fireworks are exploded at different points in the sky.

10.3.2 Local Search

This algorithm includes two types of fireworks: good and bad fireworks. As is obvious from the name, the good fireworks result in a huge population of sparks in a narrow range while the other type leads to a small population of sparks in a wide range. It is noteworthy that the sparks and range respectively denote the number of sampled solutions and the distance from the central solution. If the problem is formulated as a minimization problem, the radius of the explosion and the number of sparks relating to each firework can be stated as below:

$$A_i = \hat{A} \times \frac{f(x_i) - y_{\min} + \varepsilon}{\sum_{j=1}^{N} \left(f(x_j) - y_{\min} \right) + \varepsilon} \tag{10.37}$$

$$N_i = \hat{N} \times \frac{y_{\max} - f(x_i) + \varepsilon}{\sum_{j=1}^{N} \left(y_{\max} - f(x_j) \right) + \varepsilon} \tag{10.38}$$

In which A shows the radius of the explosion. $\hat{A}$ denotes the largest radius, N_i indicates the produced sparks by the firework i while the total number of the sparks has been represented by $\hat{N}$. Also, it is worth mentioning that the fitness of x_i is shown by $f(x_i)$ while $y_{max} = max(f(x_i))$; $y_{min} = min(f(_{xi}))$. The very low number utilized to avoid the denominator to turn to zero is indicated by ε. Moreover, two types of sparks are generally produced as explosion sparks and mutation sparks where the neighborhood search is done using the first one and the second type would be used to raise the variety of the population. For solution x_i associated with d dimensions, z($z < d$) are determined on a random basis while the value of the dimension k changes as:

$$x_{ik} = x_{ik} + deviation \tag{10.39}$$

In the case of explosion sparks, deviation = $Ai \times U(a, b)$, where $U(a, b)$ a number uniformly chosen from [a, b]. In case of the second-type sparks, i.e. mutation sparks, $deviation = Ai \times N(\mu, \sigma^2)$, where $N(\mu, \sigma^2)$ indicates a number chosen from a Gaussian distribution with μ and σ^2 as mean as variance.

10.3.3 Selection

The fireworks algorithm allocates its reproductive trials with the disparity between one solution and the remaining, while the best solution is returned to the successive generation because of the principle of holding the fittest individual. The individuals having a longer distance from others are more likely to be selected, disregarding its fitness. If K is the candidate set, the roulette wheel mechanism is employed to select the rest n-1 solutions. The probability of selecting a candidate solution $_{xi}$ is determined as follows:

$$p(x_i) = \frac{R(x_i)}{\sum_{x_j \in K} R(x_j)} \tag{10.40}$$

where $R(x_i) = \sum_{x_j \in k} \left\| x_i - x_j \right\|$.

10.3.4 Modified Fireworks Algorithm

A novel neighborhood construction method and the disparity metric are introduced in this section.

10.3.5 Local Search

The cause, beyond leading to good solutions using the Genitor algorithm, relates to its neighborhood construction method, which is also used in the modified fireworks algorithm, where the technique to produce the explosion sparks is revised.

10.3.6 Crossover Operator

It should be noted that two solutions are selected within the solution space and saved as Parent 1 and Parent 2 while the new solution would be Child. First, the crossover operator chooses K random positions in Parent 1. Then the related operator elements in Parent 2 are positioned. Elements in Parent 1 not belonging to the selected elements are directly reversed to Child with identical positions. Eventually, the free slots are allocated to the positioned elements in Parent 2 in the same order.

10.3.7 Explosion Sparks

Using the fireworks algorithm, once the spark number and the radius of the explosion are specified, all solutions are produced in its neighborhood, while no other solution is included. Nevertheless, a child solution is produced for a crossover operator using two parents, i.e. an extra solution must be included in addition to S_i. If S_{best} and S_i represent the ongoing best solution and the ongoing solution respectively, explosion sparks are produced as follows. In case $S_i = S_{best}$, S_{best} is selected as Parent 1 and another solution is selected in random as Parent 2. In case $S_i \neq S_{best}$, S_i is picked as Parent 1 and S_{best} as Parent 2. Moreover, parameter k would be equal to the explosion radius. Therefore, a child solution will be produced once k elements are chosen and the crossover operator is assigned to Parents 1 and 2.

10.3.8 Mutation Sparks

This type of spark is utilized to keep the diversity of solution and improve the local search capability. Thus the method must totally differ from the crossover operator. Three operators are proposed in [28] and the interchange operator is found to be the best. The mutation sparks are produced in this chapter with the interchange operator.

Assume Π represents the set of all permutations of the number {1,2,...,n}, and π is one of the permutations, where $\pi \in \Pi$ as follows:

$$\pi = \{\pi_1, \pi_2, \ldots, \pi_n\} \tag{10.41}$$

π_i indicates the element i in π where $\pi_i \neq \pi_j \quad (i \neq j)$.

The interchange operator selects two elements π_i and π_j in random and their locations are exchanged. π' is obtained as below provided that $i > j$.

$$\pi' = \{\pi_1, \ldots, \pi_{j-1}, \pi_i, \pi_{j+1}, \ldots, \pi_{i-1}, \pi_j, \pi_{i+1}, \ldots, \pi_n\} \tag{10.42}$$

10.3.9 Selection

The fireworks algorithm allocates the reproductive trials with the Euclidean distance between a solution and all the remaining. A proper distance between two permutations is obtained using the number of different arcs [29] provided that $\pi = \{\pi_1, \pi_2, \ldots, \pi_n\}$, and $\sigma = \{\sigma_1, \sigma_2, \ldots, \sigma_n\}$. π and σ should be transformed as follows to determine the distance.

$$\pi_P = \{(\pi_1, \pi_2), (\pi_2, \pi_3), \ldots, (\pi(n-2), \pi(n-1)), (\pi(n-1)), \pi_n)\} \tag{10.43}$$

$$\sigma_P = \{(\sigma_1, \sigma_2), (\sigma_2, \sigma_3), \ldots, (\sigma(n-2), \sigma(n-1)), (\sigma(n-1)), \sigma_n)\} \tag{10.44}$$

The distance between π and σ is determined as:

$$D(\pi, \sigma) = n - |\pi_P \cap \sigma_P| \tag{10.45}$$

10.4 Simulation Results

The presented models for the ELD and CHPS are solved using the modified fireworks algorithm, and the results are discussed in this section. The proposed framework has been coded in Matlab software run on a Core i7 Laptop with 12 GB RAM.

10.4.1 Case 1: ELD

The proposed ELD model has been implemented as a power system with a considerable number of generating units and solved using the modified fireworks algorithm. There are 13 thermal generating units operating, as well as 6 CHP units and 5 generating units. The thermal generating units and CHP units (Types 10.1–10.3) are denoted by T_1–T_{13} and CHP_{14}–CHP_{19}, while the heat-only units are indicated by B_{20}–B_{24}. The data of the generating units and the load demand data is the same as [30].

Table 10.1 represents the obtained results using the proposed method beside those reported by other references using other optimization algorithms. Although Teaching Learning Based Optimization (TLBO) and Oppositional Teaching Learning Based Optimization (OTLBO) gave better results compared to the modified fireworks algorithm, the reported operating points are infeasible, as the power generated by CHP units falls out of the related FOR. Thus, the results are not valid. The modified fireworks algorithm has reached the best solution at which the total cost of the system for satisfying the load demand is $57 963.9.

10.4.2 Case 2: CHPS

This case study uses the same data as the ED case, and it is solved using the modified fireworks algorithm. Only thermal units T_1–T_3 and T_{10}–T_{11} are used. Other units are decommitted for maintenance. Furthermore, the electrical and heat load demand patterns over the 24 hours are demonstrated in Figure 10.16.

The electrical peak load occurs at hour 18, and the heat peak load occurs at hour 1, while the electrical load demand increases over the day while the heat load demand decreases during the day. The optimal operating points of the generating units over the 24 hours are determined to take into account the thermal constraints of the thermal units, i.e. RU and RD constraints. Figure 10.17 shows the convergence of the modified fireworks algorithm for 10 runs.

It is worth mentioning that a sensitivity analysis has also been done to assess the total cost versus different load demand from 0.75 of the original load to 1.25 times the original load demand. Table 10.2 represents the results obtained.

A sensitivity analysis has been carried out to evaluate the performance modified fireworks algorithm in reaching the optimal solutions. To this end, the program has been run 10 times, taking into consideration different number sparks from 10 to 30 and three different scenarios. If the number of sparks is 10, the optimal solution would be obtained only in one of the 10 runs. In other words, the rate of achieving the optimal solution is 10%. By increasing the number of sparks to 20, this value increases to 40%. Finally, if 30 sparks are considered, all optimal solutions are obtained. The average convergence time has also experienced an incremental trend. Table 10.3 represents the brief results.

10.5 Conclusion

This chapter investigated the optimal short-term CHP scheduling problem. The proposed power system includes different generation technologies as thermal generating units, CHP units as well as heat-only units. The CHP units, unlike other units, are associated with much more complexity regarding their FOR,

Table 10.1 Simulation results obtained by different techniques for case study 4.

Output	TLBO[a] [31]	OTLBO[a] [31]	CPSO [5]	TVAC-PSO [5]	GSA [4]	Modified fireworks
PG1T	628.324	538.5656	680.0000	538.5587	538.5150	628.3185
PG2T	227.3588	299.2123	0.0000	224.4608	224.4727	143.1414
PG3T	225.9347	299.1220	0.0000	224.4608	224.4611	143.1414
PG4T	110.3721	109.9920	180.0000	109.8666	109.8666	159.7331
PG5T	110.2461	109.9545	180.0000	109.8666	109.8666	159.7331
PG6T	160.1761	110.4042	180.0000	109.8666	109.9008	159.7331
PG7T	108.3552	109.8045	180.0000	109.8666	109.8666	159.7331
PG8T	110.5379	109.6862	180.0000	109.8666	109.8666	159.7331
PG9T	110.5672	109.8992	180.0000	109.8666	109.8666	159.7331
PG10T	75.7562	77.3992	50.5304	77.5210	77.5210	40.0000
PG11T	41.8698	77.8364	50.5304	77.5210	77.5341	40.0000
PG12T	92.4789	55.2225	55.0000	120.0000	120.0000	55.0000
PG13T	57.5140	55.0861	55.0000	120.0000	120.0000	55.0000
PG14CHP	82.5628	81.7524	117.4854	88.3514	92.5632	81.0000
PG15CHP	41.4891	41.7615	45.9281	40.5611	40.0050	40.0000
PG16CHP	84.7710	82.2730	117.4854	88.3514	84.4916	81.0000
PG17CHP	40.5874	40.5599	45.9281	40.5611	40.0079	40.0000
PG18CHP	10.0010	10.0002	10.0013	10.0245	10.0000	10.0000
PG19CHP	31.0978	31.4679	42.1109	40.4288	41.1998	35.0000

Output	TLBO[a] [31]	OTLBO[a] [31]	CPSO [5]	TVAC-PSO [5]	GSA [4]	Modified fireworks
PH14CHP	105.9125	105.2219	125.2754	108.9256	111.2790	104.8000
PH15CHP	76.2843	76.5205	80.1175	75.4844	74.9980	75.0000
PH16CHP	106.9125	105.5142	125.2754	108.9256	106.7495	104.8000
PH17CHP	75.5061	75.4833	80.1174	75.4840	74.9978	75.0000
PH18CHP	39.9986	39.9999	40.0005	40.0104	40.0000	40.0000
PH19CHP	18.2205	18.3944	23.2322	22.4676	22.8181	20.0000
PH20B	468.2278	468.9043	415.9815	458.7020	458.8811	470.4000
PH21B	59.9867	59.9994	60.0000	60.0000	60.0000	60.0000
PH22B	59.9814	59.9999	60.0000	60.0000	60.0000	60.0000
PH23B	119.6074	119.9854	120.0000	120.0000	120.0000	120.0000
PH24B	119.6030	119.9768	120.0000	120.0000	120.0000	120.0000
TC ($)	58 006.9992	57 856.2676	59 736.2635	58 122.7460	58 121.8640	57 983.9000

[a] Infeasible.

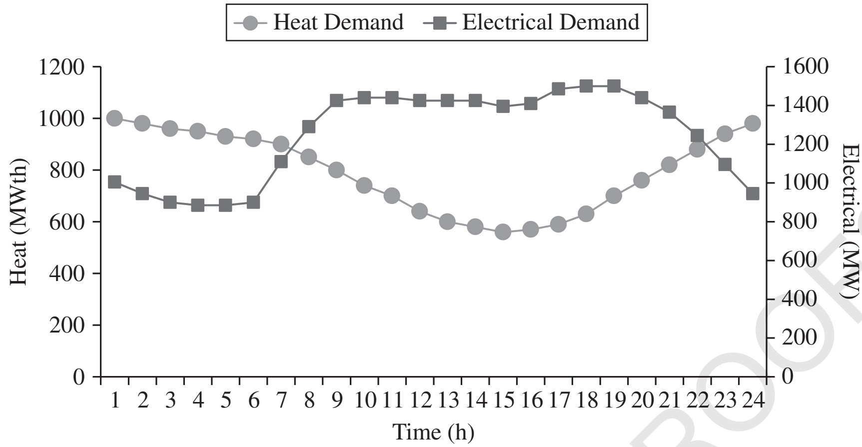

Figure 10.16 Daily electrical and heat load demand.

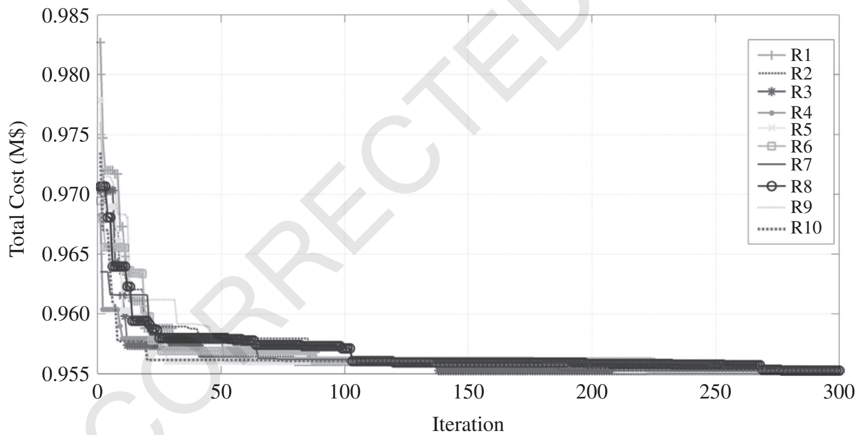

Figure 10.17 Convergence trends of the modified fireworks algorithm for 10 runs.

which can be either a convex or a non-convex plane. This chapter proposed a decomposition technique for decomposing the non-convex FORs to multiple convex FORs. The modified fireworks algorithm was also used to solve the problem presented and its performance was verified through a sensitivity analysis and by comparing the results obtained with those derived by other optimization algorithms.

Table 10.2 Sensitivity analysis results.

Load	Total Cost ($)
0.75	838 087.2092
0.80	856 810.6816
0.85	881 030.8993
0.90	905 478.8464
0.95	925 915.8465
1.00	955 226.5588
1.05	981 142.8492
1.10	1 006 999.430
1.15	1 032 972.547
1.20	1 067 069.007
1.25	1 092 448.790

Table 10.3 Brief results of the sensitivity analysis.

Number of sparks	Minimum cost ($)	Maximum cost ($)	Average cost ($)	Rate of achieving the optimal solution	Average solution time (s)
10	955 226.5588	957 383.9578	956 248.2390	10	96.65
20	955 226.5588	957 301.9621	955 974.6812	40	184.61
30	955 226.5588	955 226.5588	955 226.5588	100	295.98

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