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Solution to the unit commitment problem using an artificial neural network

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Abstract: This paper proposes a real-time solution to the unit commitment problem by considering different constraints like ramp-up rate, unit operation emissions, next hours load, and minimum down time. In this method, an optimized trade-off between cost and emission has been taken into consideration. The effectiveness of the proposed method was verified by the significant outcomes demonstrated.

Key words: Unit commitment, artificial neural network, genetic algorithm

1. Introduction

Fast growing load in power systems associated with a large gap between heavy and light load periods, generation scheduling, and the unit commitment (UC) problem has become a crucial issue in the operation time horizon. The UC problem has always been an important research challenge in power systems, especially under a restructured environment. In a vertically integrated power system, UC determines when to start up or shut down units and how to dispatch online generators over a given scheduling horizon in order to minimize the operating costs, satisfying the prevailing constraints such as load balance, system reserve requirement, ramp rate limits, and minimum up/down time limits [1–4]. Since the UC is a mixed integer program, it is very hard to get an exact optimal solution. It has been viewed as a very complex optimization problem and variant methods have been implemented to solve such a complicated problem, either using classical optimization or heuristic as well as hybrid techniques. Dynamic programming is the earliest conventional optimization method that can be applied to solve the dissimilar size UC problem. The other classical optimization methods are as follows: priority list [5], Lagrangian relaxation, mixed integer programming [6], and branch and bound. The classical optimization techniques, in general, might not be able to find a solution within a significant computational time for the medium or large scale UC problem. These limitations have been redounded to introduce the heuristic optimization methods. Emerging metaheuristic and evolutionary algorithms in the modern optimization technique, such as simulated annealing, tabu search, fuzzy logic, genetic algorithm (GA), artificial neural network (ANN) [7], and ant colony [8], have been used to solve the UC problem. Moreover, in some methods, more than one algorithm has been incorporated together, forming a hybrid technique to meet the industry requirements. The hybrid methods are also applied to handle more complicated constraints and are claimed to have a better performance. On one hand, evolutionary algorithms may seem simple but their

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solution might be suboptimal, and on the other hand, they might be complicated with more accurate results. Hybrid methods such as fuzzy dynamic programming and neural network [9], genetic-based neural network, Lagrangian relaxation associated with GA [10], and annealing GA [11] are used to tackle the UC problem. In [12], 3 evolutionary computation techniques, namely steady-state GAs, evolutionary strategies, and differential evolution for the UC problem, were compared, and it was concluded that all of these approaches are applicable to the UC problem.

The proposed method in [13] utilizes neural networks to generate a preschedule according to the input load profile and then refines the schedule, where the commitment states of some of the units are uncertain, using a dynamic search. The approach taken in [14] utilizes the Hopfield neural network. In that approach, a large number of inequality constraints included in the UC are handled by the dedicated neural network instead of including them in the energy function. Once the states of the generators are determined by the network, their outputs are adjusted according to their priority order in fuel cost per unit output. A complete list of the techniques used to solve the UC problem with their abbreviations is presented in Table 1.

Table 1. Abbreviations of the UC solution techniques.

SPL	Stochastic priority list [22]
EP	Evolutionary programming [23]
PSO	Particle swarm optimization [24]
BPSO	Binary particle swarm optimization [26]
PSO-LR	Particle swarm optimization combined with Lagrangian relaxation [27]
LR	Lagrangian relaxation [27]
LRGA	Lagrangian relaxation combined with genetic algorithm [28]
DP	Dynamic programming [28]
ALR	Augmented Lagrangian relaxation [28]
GA	Genetic algorithm [29]
BCGA	Binary coded genetic algorithm [31]
ICGA	Integer coded genetic algorithm [31]
MA	Memetic algorithm [32]
PM	Proposed method [21]
UCPOZ	Unit commitment considering prohibited operating zone [21]
ANN	Artificial neural network

In this paper, a real-time approach considering next hours demand by minimizing the operating costs and unit emissions using an ANN is presented. On the other hand, in the proposed formulation, a new objective function that comprises the start-up cost is used in order to select the best chromosomes to get better results. Hence, at first, units with less start-up cost are selected and then generation units with a higher start-up cost may have a chance to be turned on in order to minimize the total scheduling horizon costs. Eventually, the objective function is modeled using a neural network such that by instantaneous variation of the load demand, the neural network algorithm finds a real-time solution for the UC problem in a very short time.

2. Materials and methods

UC involves determining the generation outputs of all of the units from an initial hour to satisfy the load demands associated with a start-up and shut-down schedule over a time horizon. The objective is to find the optimal schedule, such that the total operating costs can be minimized while satisfying the load demand, spinning the reserve requirement as well as other operational constraints.

2.1. Objective function

The outage cost as well as the fuel cost of the generation units should be considered in power system operation as an objective function of a UC problem. The objective function is a function that comprises the fuel costs of the generating units, the start-up costs of the committed units, and the shut-down costs of the decommitted units. The start-up cost is presented in 2 schemes, hot start-up costs (HSCs) and cold start-up costs (CSCs), while the shut-down cost is assumed to be fixed. The objective function in common form is expressed by Eq. (1).

$$\begin{aligned} Minimize \quad & \{\sum_{t=1}^{T}\sum_{i=1}^{N} F_{i,t}(p_{i,t}^{o}) * u_{i,t} \\ & + \sum_{t=1}^{T}\sum_{i=1}^{N} SUC_{i,t} * u_{i,t} * (1-u_{i,t-1}) \\ & + \sum_{t=1}^{T}\sum_{i=1}^{N} SDC_{i,t} * u_{i,t-1} * (1-u_{i,t})\} \end{aligned} \tag{1}$$

Here, $P_{i,t}^{o}$ is the power output of unit i at hour t, $u_{i,t}$ is the on or off status of unit i at hour t, SUC$_{i,t}$ and SDC$_{i,t}$ are respectively the start-up cost and the shut-down cost of unit i at time t, N is the number of units, and T is the UC horizon.

The fuel costs of the generating units and the major components of the operating costs for the thermal units are generally given in a quadratic form, as is shown in Eq. (2). Operating cost coefficients can be given or they might be estimated using bidding strategies [15].

$$F_{i,t}(P_{i,t}^{o}) = a_i + b_i P_{i,t}^{o} + c_i (P_{i,t}^{o})^2 \tag{2}$$

Here, a_i, b_i, c_i are fuel cost coefficients for unit i.

The start-up cost is defined as follows:

$$SUC_{i,t} = \begin{cases} HSC_i, & \text{if} \quad T_{i,t}^{D} \le MD_i^{ON} \le T_{i,t}^{D} + CST_i \\ CSC_i, & \text{if} \quad MD_i^{ON} > T_{i,t}^{D} + CST_i \end{cases}, \tag{3}$$

where HSC$_i$ and CSC$_i$ are the hot start-up cost and cold start-up cost, respectively; $T_{i,t}^{D}$ is the minimum down time of unit i; MD_i^{ON} is the duration during which the ith unit is continuously on; and CST_i is the cold start time of unit i.

2.2. Operational limitation and constraints

The minimization of the objective function is subjected to a number of system and unit constraints, such as power balance, spinning reserve capacity of the generating units, prohibited operating zones (POZs), and minimum up/down time limit, as well as spinning reserve requirement. The initial conditions need to be considered in the scheduling problem.

2.2.1. Initial conditions

The initial conditions of the generating units include the number of hours that a unit has consequently been online or offline and its generation output at an hour before the scheduling.

2.2.2. Power balance constraint

$$\sum_{i=1}^{N} (P_{i,t}^{o}) * u_{i,t} = D_t \quad 1 \leq t \leq T \ , \ i \in N \tag{4}$$

Here, D_t is the demand during hour t.

2.2.3. Unit output limit

$$\begin{aligned} &\underline{P}_{i,t} * u_{i,t} \leq P_{i,t}^{o} * u_{i,t} \leq \overline{P}_{i,t} * u_{i,t} \\ &1 \leq t \leq T \ , \ i \in N \end{aligned} \tag{5}$$

Here, $\underline{P}_{i,t}$ and $\overline{P}_{i,t}$ are the minimum generation and maximum generation of unit i, respectively.

2.2.4. Spinning reserve

$$\sum_{i=1}^{N} (\overline{P}_{i,t}) * u_{i,t} \geq D_t + SR_t \quad 1 \leq t \leq T \ , \ i \in N \tag{6}$$

Here, SR_t is the spinning reserve requirement at time t.

2.2.5. Unit ramp-up constraint

$$\begin{aligned} &P_{i,t}^{o} \leq \overline{P}_{i,t} \\ &\overline{P}_{i,t} = Min\{P_{i,t-1}^{o} + RUR_i, \overline{P}_i\} \\ &1 \leq t \leq T \ , \ i \in N \end{aligned} \tag{7}$$

Here, RUR_i is the ramp-up rate limit of unit i.

2.2.6. Unit ramp-down constraint

$$\begin{aligned} &\underline{P}_{it} \leq P_{i,t} \\ &\underline{P}_{it} = Max\{P_{i,t-1}^{o} - RDR_i, \underline{P}_i\} \\ &1 \leq t \leq T \ , \ i \in N \end{aligned} \tag{8}$$

Here, RDR_i is the ramp down rate limit of unit i.

2.2.7. Prohibited operating zone

Some online generating units have generation limits, which cannot be exceeded at any time [16]. Moreover, a typical thermal unit may have a steam valve in operation or a vibration in a shaft bearing, which may result in interference and discontinue the input–output performance-curve sections, called the POZ, as shown in Figure 1.

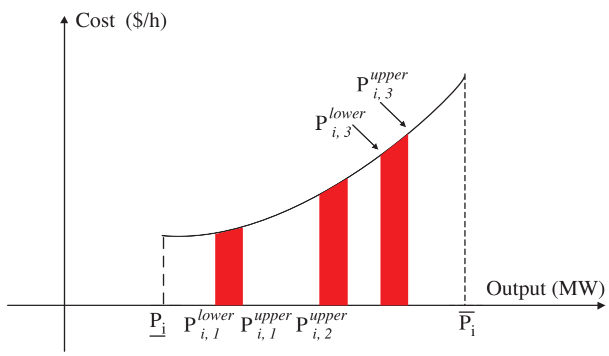

Figure 1. Prohibited operating zones and output limit of a generator.

Therefore, in practical operation, adjustment of the generation output of a unit must avoid all capacity limits and unit operations in the POZ. The feasible operating zones of a unit can be described as follows:

$$\begin{cases} \underline{P}_i \leq P_i^o \leq P_{i,1}^{Lower} \\ P_{i,j-1}^{Upper} \leq P_i^o \leq P_{i,j}^{Lower} & , \; j = 2, \ldots, PZ_i \\ P_{i,PZ_i}^{Upper} \leq P_i^o \leq \bar{P}_i \end{cases} , \tag{9}$$

where $P_{i,j}^{Lower}$ and $P_{i,j}^{Upper}$ are the lower and upper bounds of the jth prohibited zone of unit i, and PZ$_i$ is the number of prohibited zones of unit i.

2.2.8. Minimum up time limit

The minimum up time limit is the minimum number of hours that a unit must be continuously online since it has been turned on.

$$MD_i^{ON} \geq T_i^U \tag{10}$$

Here, MD_i^{ON} is the duration during which the ith unit is continuously on.

2.2.9. Minimum down time limit

The minimum down time limit is the minimum number of hours that a unit must be continuously offline since it has been turned off.

$$MD_i^{OFF} \geq T_i^D \tag{11}$$

Here, MD_i^{OFF} is the duration during which the ith unit is continuously off.

2.2.10. Solution methodology

The optimization technique consists of some steps that are shown in Figure 2a, which are explained in the following steps. In each step, the related constraints are taken into account, while the objective function associated with all of the constraints is minimized via the GA. Finally, all of the steps have been modeled using a neural network, such that by instantaneous variation of the load demand, the neural network algorithm finds a real-time solution for the UC problem in a very short time.

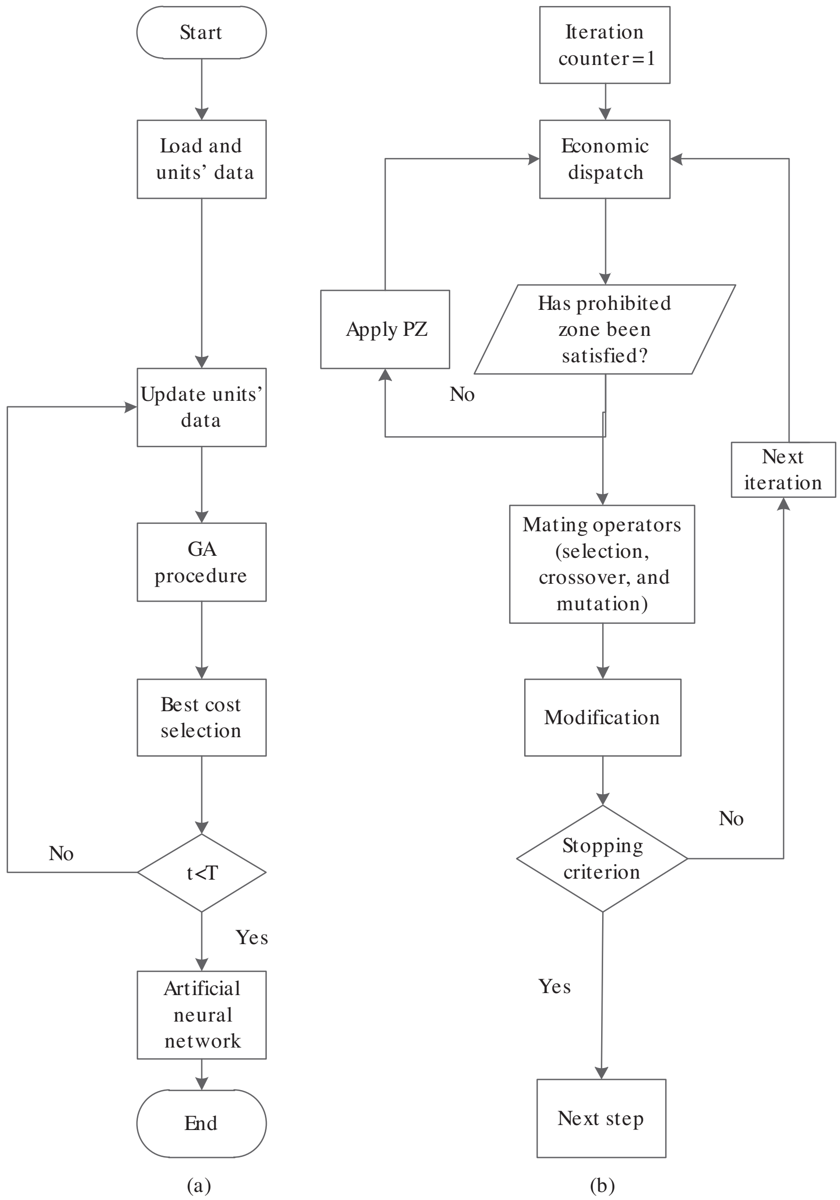

Figure 2. a) The main flowchart of proposed method (UCPOZ) and b) the GA procedure considering the POZ limit.

1. Call load and unit data.

2. Initialization: At this step, an initial population is generated according to Eqs. (5), (7), (10), and (11), such that some information for the first hour is obtained from the initial condition. In order to have an efficient program, the demands of the next T_i^D hours should be taken into consideration. When a unit is turned off, its status cannot be changed for T_i^D hours, and while satisfying the next T_i^D hours of demand, exclusion of this unit should be examined. If it is not satisfied for any of the next T_i^D hours, scheduling will be referred to the previous hour for rescheduling, in which the later unit should be kept online [17].

3. Update unit data: In this step, the units' data, such as the time that a unit has continuously been on/off according to the previous hour's scheduling, are updated.

4. GA procedure: The GA is a random and robust search technique that guides a population towards an optimum using the principles of natural evolution. This process is facilitated through a fitness evaluation procedure that determines the fitness value of each member of the population, the so-called chromosome. Each chromosome contains a number of genes. In this simulation, the chromosome corresponds to a plant and a gene corresponds to a unit. The robustness of the GA and its capability across a broad range of problems make the GA a general problem-solving technique in many applications [18]. Hence, in this paper, according to the complexity of UC considering the POZ (UCPOZ), the GA is used to solve this complicated and nonconvex optimization problem. The flowchart of the proposed GA-based solution approach for UCPOZ is shown in Figure 2b, which includes the following steps:

   (a) Initialize the iteration counter as a stopping criterion: In this paper, according to the number of units, the number of iterations is set to 80, and at first, the iteration counter is set to 1.

   (b) Economic dispatch (ED): ED determines the output of all of the online units with the objective of the minimum total operating cost at a given hour, which is subjected to the power balance constraint in Eq. (4) and the output limits in Eq. (5). For each chromosome of the generated population in step 2 of the main flowchart, ED is applied and the output power of each gene of the chromosome is obtained. A lambda iteration method is applied in this paper to determine the optimal ED.

   (c) Prohibited zone check: After ED, for each gene of the chromosome, the POZ check is taken into consideration. If any of the genes have violated the POZ, the POZ is applied to that gene and ED is repeated for the aforementioned chromosome.

   (d) Fitness evaluation: In this step, the fitness value of each chromosome should be calculated. In order to accelerate the convergence of the proposed method, the fitness function is adopted as follows:

$$Adopted\, fitness\, function = \frac{A}{1 + Cost(chr, itr)}, \tag{12}$$

   where A is a big positive number (assumed 1E+4) and *chr* and *itr* are the chromosomes and iteration counter, respectively. Thus, a modified cost function is shown by Eq. (13).

   Since in scheduling problems the objective is to minimize the operating costs, those units with more expensive start-up costs may have no chance to be turned on before they must be, while they may impose lower total operating costs. Hence, in this paper, a modified objective function is defined in order to select the best chromosomes for crossover and mutation to generate new chromosomes for achieving optimum scheduling.

$$Cost(chr, itr) = Min \sum_{t=1}^{T} \sum_{i=1}^{N} F_{i,t}(p_{i,t}) * u_{i,t} + SUC_{i,t} * u_{i,t} * (1 - u_{i,t-1})\}, \tag{13}$$

   where:

$$SUC_{i,t} = \begin{cases} CSC_{i,t} & \text{if} \quad MD_i^{OFF} > T_i^D + CST_{i,t} \\ (1 + \frac{MD_i^{OFF}}{T_i^D + CST_{i,t}})HSC & \text{if} \quad T_i^D \le MD_i^{OFF} \le T_i^D + CST_{i,t} \end{cases} . \tag{14}$$

   In this paper, the CSC is considered to be twice that of the HSC.

(e) Mating: The mating process consists of 3 operators: selection, crossover, and mutation [19].

(f) Modification: After the crossover and mutation processes for achieving feasible chromosomes, the 2 following tasks should be handled:

- Chromosome elimination: Infeasible chromosomes that cannot satisfy the system reserve requirement constraint will be eliminated as redundant.
- Chromosome modification: Since the number of chromosomes must remain constant, chromosomes with the best fitness are replaced instead of eliminating chromosomes.

(g) Stopping criterion: To stop the GA procedure, a criterion is needed; in this study, a constant number of iterations has been used.

5. Best cost selection: In this step, the chromosome with the least cost is selected and the output power for all of the genes is kept as the best answer.

   All of the steps are repeated in the scheduling time horizon.

6. After the optimization is done with the GA [20], the optimized objective function is modeled using an ANN.

2.3. Radial basis neural network

The radial basis network, in contrast with other neural networks, is composed of more neurons and needs less designing time, and is usually used for estimating functions with zero error. The radial basis network structure with R input is shown in Figure 3. This network is composed of 2 layers. The first layer inputs are 10 neurons that represent the load profile during a 24-h day and the cost coefficients. The outputs of the first layer are the inputs for the second layer and the outputs of the second layer are the generation of each unit [21].

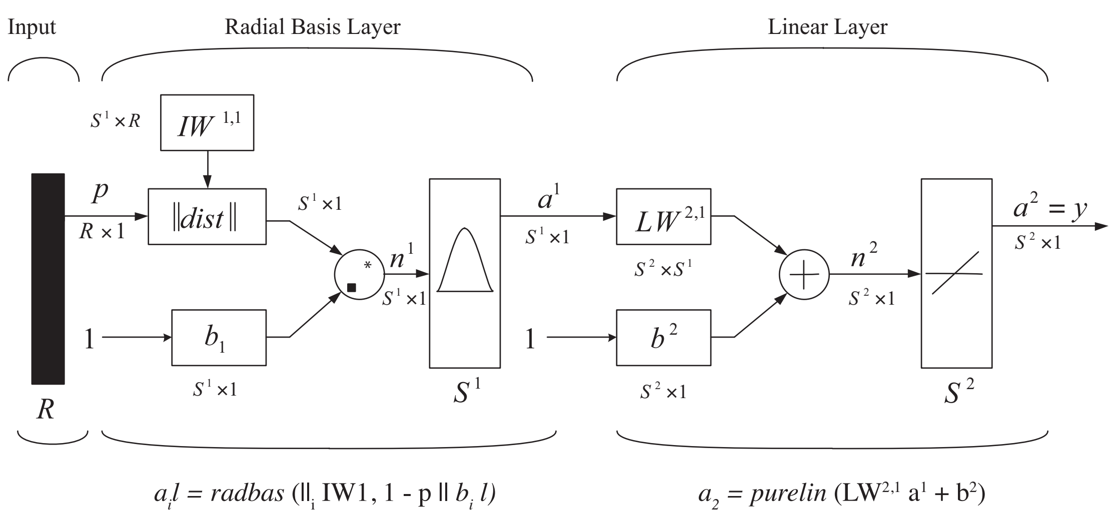

Figure 3. The radial basis network structure with R input.

The function newrb iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons have been reached. A plot of the newrb function is shown in Figure 4.

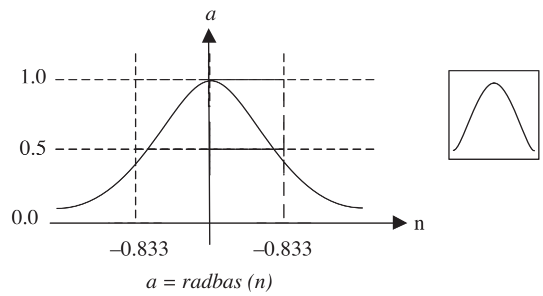

Figure 4. The newrb function.

3. Results and discussion

The proposed methodology is implemented in a standard IEEE 10-unit test system. At first the study is only about a common UC problem, and finally the POZ is taken into consideration as a practical and redundant limitation. The POZ that is employed in the paper is not an accurate representation. However, there is no great difficulty in making some changes in the formulations developed so that the proposed approach can employ a different dispatch representation.

Case 1. Standard IEEE 10-unit test system

The proposed method has been applied to solve a common UC problem, the so-called 10-unit base system, with the given data presented in Table 2 where, in this case, the POZ limitation is not considered. The result of the units' output power is given in Table 3 and the total cost comparison of several techniques is shown in Table 4.

Table 2. Unit characteristics and cost coefficients of a 10-unit base problem.

Unit no.	P_{max}	P_{min}	a	b	c	T^U	T^D	HSC	CSC	CST	Unit condition	Prohibited operating zones
1	455	150	1000	16.19	0.00048	8	8	9000	4500	5	8	[150 165], [448 453]
2	455	150	970	17.26	0.00031	8	8	10,000	5000	5	8	[90 110], [240 250]
3	130	20	700	16.6	0.002	5	5	1100	550	4	–5	—
4	130	20	680	16.5	0.00211	5	5	1120	560	4	–5	—
5	162	25	450	19.7	0.00398	6	6	1800	900	4	–6	—
6	80	20	370	22.26	0.00712	3	3	340	170	2	–3	—
7	85	25	480	27.74	0.00079	3	3	520	260	2	–3	—
8	55	10	660	25.92	0.00413	1	1	60	30	0	–1	[20 30], [40 45]
9	55	10	665	27.27	0.00222	1	1	60	30	0	–1	—
10	55	10	670	27.79	0.00173	1	1	60	30	0	–1	[12 17], [35 45]

The load demand of the 10-unit base problem is given in Table 5.

Table 3. Unit output power for the 10-unit case.

	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	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
2	245	295	370	455	455	455	455	430	455	455	455	455	455	455	455	315	260	360	455	455	455	455	425	345
3	0	0	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
4	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
5	0	0	25	40	70	40	90	25	85	162	162	162	162	85	30	25	25	25	30	162	85	145	0	0
6	0	0	0	0	20	20	20	20	20	33	68	80	33	20	0	0	0	0	0	33	20	20	20	0
7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
8	0	0	0	0	0	0	0	0	0	10	10	43	10	0	0	0	0	0	0	10	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0

Table 4. Total cost comparison of several techniques.

Total cost of the different methods							
Method	SPL	EP	PSO	BPSO	PSO-LR	LR	LRGA
Cost	$564,950	$565,352	$574,153	$565,804	$565,869	$566,107	$564,800
Total cost of the different methods							
Method	ALR	GA	BCGA	ICGA	DP	MA	PM
Cost	$565,508	$565,825	$567,367	$566,404	$565,825	$565,827	$564,703

Table 5. Load demand of the 10-unit base problem.

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

Case 2. IEEE 10-unit test system considering the POZ

In practice, each generator has its generation limit, which cannot be exceeded at any time. Moreover, a typical thermal unit may have a steam valve in operation or a vibration in a shaft bearing, which may result in interference and discontinue the inputoutput performance-curve sections, called the POZ. Hence, it seems to be essential to study the POZ as a redundant limitation. As it can be seen from the first hour, both of the units are generated in the POZ and it is difficult to change these generations according to the POZ, but using the GA is an efficient method for this purpose. The result of the units output power is given in Table 6 for a 24-h time horizon with a total operating cost of US$564,714. The POZ is a practical constraint in the UC problem and has not been considered previously in the literature. Hence, by comparison of the UCPOZ cost with the costs in Table 4, it is clearly seen that there is no main difference between them, which presents the effectiveness of UCPOZ.

The POZ employed in this paper is not an accurate representation and is given in Table 2. However, there is no great difficulty in making some changes in the formulations developed so that the proposed approach can employ different POZ representations.

Case 3. IEEE 10-unit test system UC real-time solving using an ANN

Using an ANN, the IEEE 10-unit test system was modeled. By taking the load profile and the cost coefficients as inputs and the generation of each unit as outputs, the radial basis neural network was trained, and this trained network can solve the UC problem immediately. In order to train the neural network, the load profile is changed from 700 MW to 1500 MW, with loads steps of 5 MW. With every variation of the load, the generation of each unit is obtained using the algorithm shown in Figure 2. By considering these steps, 160 different paradigms of the load are obtained. There are 140 paradigms of these load profiles, which include all of the load profile variations, used to train the neural network, and 20 of them are used in order to test the results obtained by the neural network. The results are shown in Figure 5, which shows that this procedure solves the UC problem in less than 0.02 s.

Table 6. Unit output power for the 10-unit case considering the POZ.

	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	**447.9999**	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
2	**252.0001**	295	370	455	455	455	455	430	455	455	455	455	455	455	455	315	260	360	455	455	455	455	425	345
3	0	0	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
4	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
5	0	0	25	40	70	40	90	25	85	162	162	162	162	85	30	25	25	25	30	162	85	145	0	0
6	0	0	0	0	20	20	20	20	20	33	68	**77.9999**	33	20	0	0	0	0	0	33	20	20	20	0
7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
8	0	0	0	0	0	0	0	0	0	10	10	**45.0001**	10	0	0	0	0	0	0	10	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0

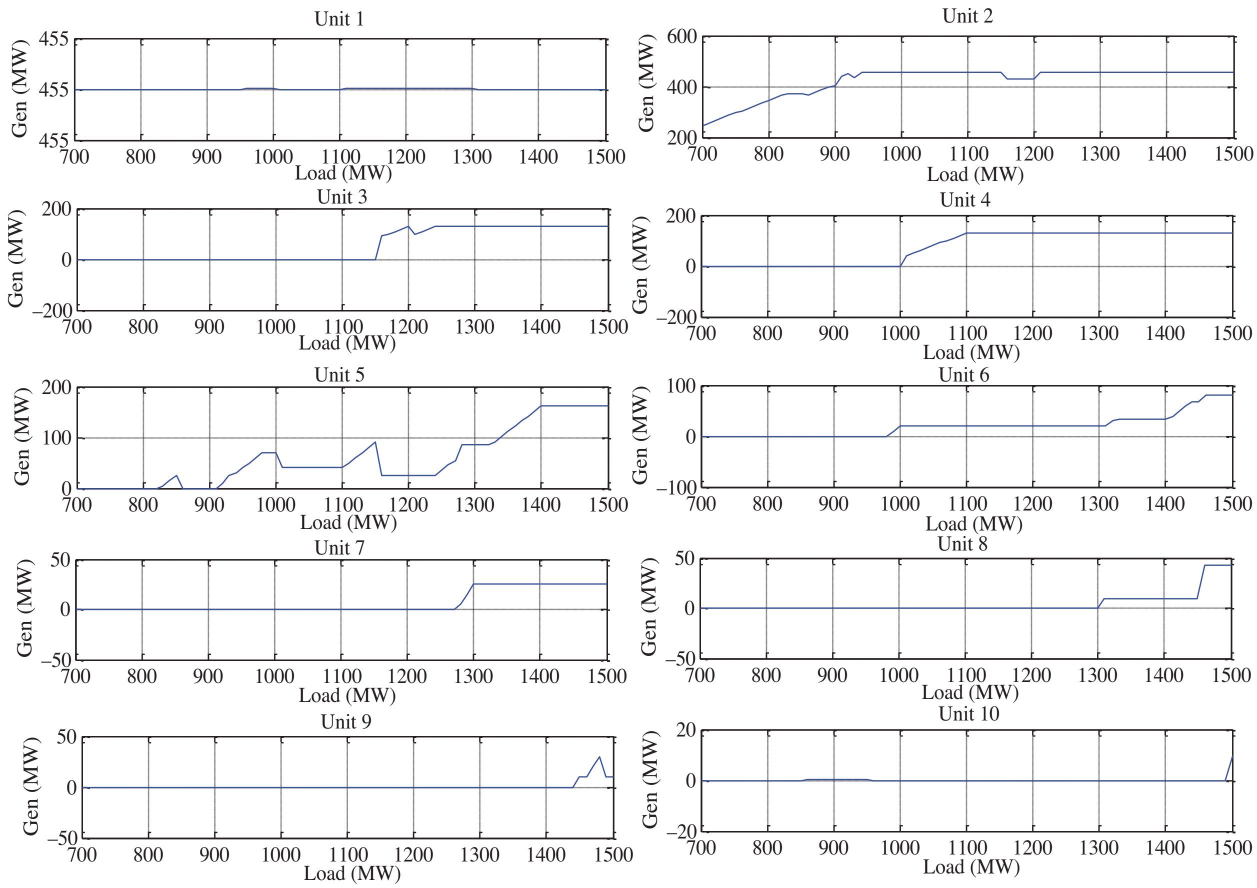

Figure 5. Generation of each unit vs. the dynamic load profile.

4. Conclusions

In this paper, a reliable and efficient method using a heuristic technique for UC as well as a scheduling problem has been presented. A new approach has been presented to select the best chromosomes via the GA, where the objective function in the GA comprised the start-up cost to give a chance to those units that have a higher start-up cost, and this yields a wide search area. The POZ, as a practical constraint, has also been considered. The proposed method has been successfully applied to a standard 10-unit system and a 10-unit system considering the POZ and the satisfactory results were compared with the other methods reported in the literature. Finally, the objective function was modeled via an ANN and the results can offer the usefulness of the proposed method, which can be considered as a practical technique. The results show that the proposed method has the following merits in both the UC problem and the UCPOZ problem: efficient searching ability, robustness in results, and real-time UC problem solving.

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