A solution to energy and environmental problems of electric power system using hybrid harmony search-random search optimization algorithm

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Abstract: In recent years, global warming and carbon dioxide (CO2) emission reduction have become important issues in India, as CO2 emission levels are continuing to rise in accordance with the increased volume of Indian national energy consumption under the pressure of global warming, it is crucial for Indian government to impose the effective policy to promote CO2 emission reduction. Challenge of supplying the nation with high-quality and reliable electrical energy at a reasonable cost, converted government policy into deregulation and restructuring environment. This research paper presents aims to presents an effective solution for energy and environmental problems of electric power using an efficient and powerful hybrid optimization algorithm: Hybrid Harmony search-random search algorithm. The proposed algorithm is tested for standard IEEE-14 bus, -30 bus and -56 bus system. The effectiveness of proposed hybrid algorithm is compared with other well-known evolutionary, heuristics and meta-heuristics search algorithms. For multi-objective unit commitment, it is found that as there are conflicting relationship between cost and emission, if the performance in cost criterion is improved, performance in the emission is seen to deteriorate.

Keywords: harmony search (HS); multi-objective unit commitment (MOUC); pattern search (PS); random search (RS); environmental sustainability engineering

1. Introduction

Today’s power system is characterized by large proportions, high interconnections and high nonlinearities, as the size of the power system is growing exponentially due to heavy demand of power...
in all the sectors viz. agricultural, industrial, residential and commercial ones. Increase in the electrical energy demand and trends in privatization and deregulation result in overloading impact on electrical grids. The situation necessitates the development of electrical grid at the same pace as the demand increases, but economical commitment and scheduling has the ability to tackle the time-varying power demand, environmental constraints and led to the full exploitation of accessible grid. In the modern power system networks, there are various generating resources like thermal, hydro, nuclear, etc. Also, the load demand varies during a day and attains different peak values. Thus, it is required to decide which generating unit to turn on and at what time it is needed in the power system network and also the sequence in which the units must be shut down keeping in mind the cost-effectiveness of turning on and shutting down of respective units. The entire process of computing and making these decisions is known as unit commitment (UC). The unit which is decided or scheduled to be connected to the power system network, as and when required, is known to be committed unit. Unit commitment in power systems refers to the problem of determining the on/off states of generating units to minimize the operating cost for a given time horizon (Kamboj, 2015).

Generators cannot be immediately turned on to meet up power demand. So, it is required that the planning of generating units must be so prepared that there is enough generation available to fulfil the load demand along with an ample reserve generation to avoid failures and malfunctions under adverse conditions. Unit commitment knob the unit generation schedule in electric power system for minimizing operational and fuel cost and satisfying system and physical constraints such as load demand and system reserve requirements over a set of time periods (Zhu, 2009). Unit Commitment Problem (UCP) is basically about finding the most suitable schedule to turn on or turn off the generating units to meet the electric power demand and at the same time keep the cost of generation as much minimum as possible. UCP is a non-linear, large-scale, mixed integer constrained optimization problem (Rajan, Mohan, & Manivannan, 2002) and happens to belong to combinatorial optimization problems. There are many constraints involved in UCP, and hence, it is quite a complex and tedious task to compute or to find the optimal solution for UCP. The scheduling of the units together with the allocation of the generation quantities which must be scheduled to meet the demand for a specific period represents the UCP. The UCP is to determine a smallest cost turn-on and turn-off plan of a set of generating units to meet a power demand while satisfying system operational and physical constraints liked with various generating units. The production cost includes fuel, start-up, no load costs and shutdown cost. The operational constraints that must be taken into consideration comprise: (1) The total power generated must meet the power demand plus system losses. (2) There must be an adequate amount of spinning reserve to cover any shortfalls in power generation. (3) The loading of each unit must be within its minimum and maximum permissible rating. (4) The minimum up and down times of each unit must be pragmatic. The unit commitment is aimed to formulate a proper generator commitment schedule for electric power system over a period of one day to one week.

The main objective of unit commitment is to minimize the total production cost over the study period and to satisfy the system and physical constraints imposed on the system such as spinning reserve, power generation-load balance, operating constraints, minimum up time and minimum down time, etc. Several conventional methods are available to solve the UCP. But all these methods need the exact mathematical model of the system and there may be a chance of getting stuck at the local optimum (Kamboj, Bath, & Dhillon, 2016).

2. Literature review

Sriyanyong and Song (2005) proposed Particle Swarm Optimization (PSO) combined with Lagrange Relaxation method for solving UCP. Mallipeddi and Suganthan (2014) provided an extensive literature survey on the algorithms developed for UCP and tried to compare their performance on some standard benchmark problems. Jeong, Park, Jang, and Lee (2009) have discussed binary Particle Swarm optimization-based approach for solving the UC problems. Ge (2010) has proposed a new approach to solve ramp rate constrained UCP by improving the method of PSO. Borghetti et al. (2001) have suggested that there is no guarantee that the Tabu search will yield the global optimal result for large systems. There is a similar method named PSO proposed in Gaing (2003a). Rajan, Mohan, and Manivannan (2003) proposed Neural-based Tabu search algorithm for the UCP and developed
an improved version of Neural-based Tabu search approach (Rajan et al., 2002). Gaing (2003b) proposed binary particle swarm optimization (BPSO). The BPSO is used to solve the combinatorial unit on/off scheduling problem for operating fuel and transition costs. The ED subproblem is solved using the lambda iteration method for obtaining the total production cost. Zhao, Guo, Bai, and Cao (2006) presented an improved particle swarm optimization algorithm (IPSO) for UC which utilizes more particles information to control the process of mutation operation. For proper selection of parameters, some new rules are also proposed. The proposed method combines LR technique to 0–1 variable. Lee and Chen (2007) presented a new approach for UCP named the iteration particle swarm optimization (IPSO). The proposed method improves the quality of solution in terms of total production cost and also improves the computation efficiency. A standard 48 unit system has been tested for validation. Samudi, Das, Ojha, Sreeni, and Cherian (2008) have presented a new approach of PSO algorithm for short-term hydrothermal scheduling (HTS) problems. The proposed algorithm is ideally suitable for hydrothermal co-ordination problems, hydroeconomic dispatch problems with unit commitment, thermal economic dispatch with unit commitment problems and scheduling of hydraulically coupled plants. Yuan, Nie, Su, Wang, and Yuan (2009) proposed a new improved binary PSO (IBPSO). The standard PSO is improved using the priority list and heuristic search to improve the MUT and MDT constraints. The 10–100 units have been tested to validate the proposed approach. Numerical performance shows that the proposed approach is superior in terms of low total production cost and short computational time compared with other published results. Although no optimization algorithm can perform general enough to solve all optimizations problems, each optimization algorithm has their own advantages and disadvantages. PSO has simple concept, easy implementation, relative robustness to control parameters and computational efficiency (Mirjalili & Lewis, 2014), although it has numerous advantages, it get trapped in a local minimum, when handling heavily constrained problems due to the limited local/global searching capabilities (Dhillon & Kothari, 2010; Mirjalili, Mirjalili, & Lewis, 2014). The limitations of the numerical techniques (Guy, 1971; Hara, Kimura, & Honda, 1966; Kerr et al., 1966) and dynamic programming method (Hobbs et al., 1988; Lowery, 1966) are the size or dimensions of the problem, large computational time and complexity in programming. The mixed integer programming methods (Tao & Shahidehpour, 2005; Venkatesh, Jamtsho, & Gooi, 2007) for solving the economic load dispatch problem fail when the participation of number of units increases because they require a large memory and suffer from great computational delay. Gradient Descent method (Mohan et al., 2002) is distracted for Non-Differentiable search spaces. The Lagrangian Relaxation (LR) approach (Guan et al., 2003) fails to obtain solution feasibility and solution quality of problems and becomes complex if the number of units is more. The Branch and Bound (BB) method (Cohen & Yoshimura, 1983) employs a linear function to represent fuel cost, start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a large practical size. An Expert System (ES) algorithm (Salam et al., 1991) rectifies the complexity in calculations and saving in computation time. But it faces the problem if the new schedule is differing from schedule in database. The fuzzy theory method (Kadam et al., 2009) using fuzzy set solves the forecasted load schedules error but it suffers from complexity. The Hopfield neural network technique (Yalcinoz et al., 1999) considers more constraints but it may suffer from numerical convergence due to its training process. The Simulated Annealing (SA) (Simopoulos & Contaxis, 2004) and Tabu Search (TS) (Mantawy et al., 1998) are powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it takes much time to reach the near-global minimum. Gravitational Search algorithm has the advantages to explore better optimized results, but due to the cumulative effect of the fitness function on mass, masses get heavier and heavier over the course of iteration. This causes masses to remain in close proximity and neutralize the gravitational forces of each other in later iterations, preventing them from rapidly exploiting the optimum (Mirjalili & Lewis, 2014). Therefore, increasing effect of the cost function on mass, masses get greater over the course of iteration and search process and convergence becomes slow. The harmony search (HS) algorithm proposed by Geem et al. (2001) is a recently developed meta-heuristics search algorithm inspired from the musical process of searching for a perfect state of harmony. HS has a novel stochastic derivative (Geem, 2008).
applied to discrete variables, which uses musician’s experiences as a searching direction and is free from divergence. It can handle discrete and continuous variables and do not require initial value setting for the variables. Also, it does not require differential gradients and has the ability to escape from local optima. HS has ability to overcome the drawback of GA’s building block theory and explicitly considers the relationship using ensemble operation (Geem, 2006a). Geem, Tseng, and Park (2005) proposed a Multi-pitch Adjusting Rate (multiple PAR) for Generalized Orienteering Problem. They proposed three PARs that are the rates of moving to nearest, second nearest and third nearest cities, respectively. Geem (2006b) presented the use of fixed parameter values, such as HMS, HMCR, PAR and NI, while bandwidth was set to a range from 1 to 10% of the total value data range. Mahdavi, Fesanghary, and Damangir (2007) proposed Improved Harmony Search (IHS) algorithm, which includes dynamic adaptation for both pitch adjustment rate (PAR) and bandwidth (bw) values. But it faces the difficulty of determining the lower and upper bound of automatic bandwidth (bw), which was overcome by Global-best harmony search (GHS) algorithm proposed by Omran and Mahdavi (2008). GHS algorithm incorporates the PSO concept, global best particle, by replacing the bw parameter altogether and adding a randomly selected decision variables from the best harmony vector in HM. Mukhopadhyay, Roy, Das, and Abraham (2008) suggested that bw will be the standard deviation of the current population when HMCR is close to 1. Degertekin (2008) proposed a new HM initialization technique that generated two times of HMS initial harmonies but placed only the best HMS of these into the initial HM. Chakraborty, Roy, Das, Jain, and Abraham (2009) proposed Differential Harmony Search algorithm, a new improvement to HS through inspiring the Differential Evolution (DE) mutation operator, which replaces the pitch adjustment operation in classical HS with a mutation strategy borrowed from the DE (DE/rand/1/bin class) algorithm. Hasançebi, Erdal, and Saka (2009) and Saka and Hasançebi (2009) proposed a new adaptation for HS by making both HMCR and PAR change dynamically during the improvisation process of HS. This step is to make the selection of these parameter values problem independent, therefore, improves the performance of HS in finding an optimal solutions. Kattan, Abdullah, and Salam (2010) used HS as a new training technique for feed-forward artificial neural networks (ANN). Wang and Huang (2010) proposed a new variation of HS algorithm that focuses on the dynamic selection of bw and PAR parameters. Al-Betar, Khader, and Liao (2010a) also proposed a Multi-pitch Adjusting Rate strategy for enhancing the performance of HS in solving course timetabling problem. They proposed eight procedures instead of using one PAR value, each of which is controlled by its PAR value range. Each pitch adjustment procedure is responsible for a particular local change in the new harmony. Furthermore, the acceptance rule for each pitch adjustment procedure is changed to accept the adjustment that leads to a better or equal objective function. Moved from these innovative ideas, the research proposal for hybrid combination of Harmony Search (HS) and Random Search Algorithm has been taken into consideration to solve the UCP of electric power system.

3. UCP formulation

3.1. Cost minimization

The foremost objective of unit commitment is to find the optimal schedule for operating the available generating units to regulate the total operating and generation cost of electric power utilities. Total operating cost of power generation includes fuel cost, shutdown and start-up costs. The fuel costs are calculated using the data of generating unit characteristics such as fuel price information, heat rate of generating utilities, turn-on, turn-off and initial status of units, which is mathematically, a quadratic, non-smooth and non-convex equation of power output of each generator at each hour and can be determined by Economic Load Dispatch (ELD) (Kerr et al., 1966), as represented below:

\[ F_{\text{cost}}(P_i) = a_i P_i^2 + b_i P_i + c_i \]  \hspace{1cm} (1)

where \(a_i, b_i\), and \(c_i\) are the fuel cost coefficients of \(i\)th generating units.

The total fuel cost over the given time horizon “H” is
where $U_i(h)$ is the position or status of $i$th unit at $h$th hour. Start-up cost is warmth-dependent. Start-up cost is that cost which occurs while bringing the thermal generating unit online. It is expressed in terms of the time (in hours) for which the units have been shut down. On the other hand, shutdown cost is a fixed amount for each unit which is shut down. Mathematically, start-up cost can be expressed as:

$$TFC = \sum_{h=1}^{H} \sum_{i=1}^{G} \left[(a_i P_i^2 + b_i P_i + c_i) \ast U_i(h) + SUC_i(h) \ast (1 - U_{i,h-1}) \ast U_i(h)\right]$$  \hspace{1cm} (2)

where $U_i(h)$ is the position or status of $i$th unit at $h$th hour. Start-up cost is warmth-dependent. Start-up cost is that cost which occurs while bringing the thermal generating unit online. It is expressed in terms of the time (in hours) for which the units have been shut down. On the other hand, shutdown cost is a fixed amount for each unit which is shut down. Mathematically, start-up cost can be expressed as:

$$SUC_i(h) = \begin{cases} HSC_i; & \text{for } MDT_i \leq MDT_i^{ON} \leq (MDT_i + CSH_i) \\ CSC_i; & \text{for } MDT_i^{ON} < (MDT_i + CSH_i) \end{cases} (i \in G; h = 1, 2, 3, ..., H)$$  \hspace{1cm} (3)

where $CSC_i$ and $HSC_i$ are the cold start-up and hot start-up cost of $i$th unit, respectively, and $MDT_i$ is the minimum downtime of $i$th unit, $MDT_i^{ON}$ is the number of hours that $i$th unit has been online since it was turned ON earlier and $CSH_i$ is the cold start hour of unit $i$. The various constraints linked with UCP are mentioned below.

3.1.1. Load balance or power balance constraints

The load balance or system power balance constraint requires that the sum of generation of all the committed units at $h$th hour must be greater than or equal to the demand at a particular hour “$h$”.

$$\sum_{i=1}^{NG} P_{i,h} U_{i,h} = D_h,$$  \hspace{1cm} (4)

3.1.2. Spinning reserve constraints

Considering the important aspect of reliability, there is a provision of excess capacity of generation which is required to act instantly when there is a failure of already running unit or sudden load demand. This excess capacity of generation is known as Spinning Reserve and mathematically given as:

$$\sum_{i=1}^{N} P_{i,max,h} U_{i,h} \geq D_h + R_h.$$  \hspace{1cm} (5)

3.1.3. Thermal constraints

A thermal generation unit needs to undergo gradual temperature changes and thus it takes some period of time to bring a thermal unit online. Also, the operation of a thermal unit is manually controlled. So a crew is required to perform the operation and maintenance of any thermal unit. This leads to many restrictions in the operation of thermal unit and thus it gives rise to many constraints.

3.1.4. Minimum uptime

If the units have already been shut down, there will be a minimum time before they can be restarted. This constraint is given as:

$$X_{i}^{on}(t) \geq MUT_i,$$ \hspace{1cm} (6)

where $X_{i}^{on}(t)$ is the duration for which unit $i$ is continuously ON (in hrs) and $MUT_i$ is the unit $i$ minimum uptime (in hrs).

3.1.5. Minimum down time

Once the unit is decommitted, there is a minimum time before it can be recommitted. This constraint is given as:

$$X_{i}^{off}(t) \geq MDT_i,$$ \hspace{1cm} (7)

$$NG \times P_{i,h} U_{i,h} = D_h.$$  \hspace{1cm} (4)

$$\sum_{i=1}^{N} P_{i,max,h} U_{i,h} \geq D_h + R_h.$$  \hspace{1cm} (5)

$$X_{i}^{on}(t) \geq MUT_i,$$ \hspace{1cm} (6)

$$X_{i}^{off}(t) \geq MDT_i,$$ \hspace{1cm} (7)
where $X_i^{off}(t)$ is the duration for which unit $i$ is continuously OFF (in hrs) and $MDT_i$ minimum downtime (in hrs).

### 3.1.6. Crew constraints

If a plant consists of two or more units, they cannot be turned on at the same time since there are not enough crew members to attend both units while starting up.

### 3.1.7. Maximum and minimum power limits

Every unit has its own maximum/minimum power level of generation, beyond and below which it cannot generate.

$$P_{i,\text{min}} \leq P_{ih} \leq P_{i,\text{max}}.$$  \hfill (8)

### 3.1.8. Initial operating status of generating units

The initial operating status of every unit should take the last day’s previous schedule into account, so that every unit satisfies its minimum up/down time.

### 3.2. Emission minimization

To obtain the generation schedule that minimizes the total emission, the objective function described in (1) can be reformulated as:

$$F_{\text{total\ emission}}(P) = \alpha_i P_i^2 + \beta_i P_i + \gamma_i$$  \hfill (9)

where $\alpha_i$, $\beta_i$, and $\gamma_i$ are the emission coefficients of $i$th generating units.

The total emission over the given time horizon “$H$” is

$$TFC = \sum_{h=1}^{H} \sum_{i=1}^{G} \left[ (\alpha_i P_i^2 + \beta_i P_i + \gamma_i) \ast U_{ih} + \text{SUC}_{ih} \ast (1 - U_{ih-1}) \ast U_{ih} \right].$$  \hfill (10)

### 3.3. Multi-objective problem formulation

Many real-world applications involve simultaneous optimization of several objective functions, which are often competing or conflicting with each other, and subject to a number of equality and inequality constraints. In general, these multi-objective problems can be formulated as follows:

minimize $f_p(U)$, \hspace{1cm} $p = 1, 2, 3, ..., P$  \hfill (11)

Subject to

$$\begin{cases} v_q(U) = 0, & q = 1, 2, 3, ..., Q \\ w_r(U) \leq 0, & r = 1, 2, 3, ..., R \end{cases}$$  \hfill (12)

where $f_p(U)$ is the $p$th objective function, $U$ is a decision vector that represents a solution, $P$ is the number of objectives, $v_q$ is the $q$th of the $Q$ equality constraints and $w_r$ is the $R$th of the inequality constraints.

The objective functions $f_p(U)$ must be evaluated in correspondence of each decision variable vector $U$ in the search space. The final goal is to identify a set of optimal decision variable vectors $U_m$, \hspace{1cm} $m = 1, 2, 3, ..., M$, instead of a single optimal solution. In this set of optimal solutions, no one can be regarded to be better than any other with respect to all the objective functions.

The comparison of solutions may be achieved in terms of the concepts of Pareto optimality and dominance (Montawy et al., 1998): taking a minimization problem as example, $U_1$ solution is regarded to dominate solution $U_2(U_1 > U_2)$ if both the following conditions are satisfied:
If any of the above two conditions is violated, the solution does not dominate the solution, and is said to be non-dominated by. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set, and the corresponding values of the objective functions form the so-called Pareto-optimal front in the objective functions space. The goal of a multi-objective optimization algorithm is to guide the search for finding solutions of the Pareto-optimal set.

MOUCP can be formulated as a non-linear mixed combinatorial and continuous multi-objective optimization problem, as follows:

\[
\text{minimize } [f_{\text{cost}}(P, U), f_{\text{Emission}}(P, U)]
\]

Subject to: \( v(P) = 0 \)

\[w(P, U) \leq 0\]

where \( P = (P_1^1, P_{21}^1, ..., P_{N1}^1, ..., P_{1P}^{T_{\text{max}}}, P_{2P}^{T_{\text{max}}}, ..., P_{NP}^{T_{\text{max}}}) \) is an \( N \times T_{\text{max}} \) matrix with the powers \( P_i^t \) as its elements and \( U = (U_1^1, U_{21}^1, ..., U_{N1}^1, ..., U_1^{T_{\text{max}}}, U_{21}^{T_{\text{max}}}, ..., U_{N1}^{T_{\text{max}}}) \) is an \( N \times T_{\text{max}} \) matrix with the commitment states \( U_i^t \) as its elements.

4. Materials and methods

4.1. Hybrid harmony search-random search algorithm

Harmony Search (HS) is a population-based meta-heuristics search algorithm inspired from the musical process of searching for a perfect state of harmony. HS has been proposed by Geem, Kim, and Loganathan (2001). The pitch of each musical instrument determines the aesthetic quality, just as the fitness function value determines the quality of decision variables. In the musical improvisation process, all players sound pitches within possible range together to make one harmony. If all the pitches make a good harmony, each player stores in his memory that experience and the possibility of making a good harmony is increased next time. The same thing in optimization, the initial solution is generated randomly from decision variables within the possible range. If the objective function values of these decision variables are good to make a promising solution, then the possibility to make a good solution is increased next time. Random Search Algorithm is a derivative-free method for continuous domain, which is based on direct search and most suitable for Stochastic and Global optimization problem. In the proposed algorithm, HS is combined with Random Search algorithm for random population search. The major steps of proposed hybrid algorithm are mentioned below:

- Initialization of harmony memory (HM)
- Harmony memory considering (HMC) rule
- Pitch adjusting rate (PAR)
- Random initialization rule
- Harmony memory updating
- Ensemble consideration
Step-I: Initialization of harmony memory (HM)

The initial population HM consists of HMS vectors is generated randomly (Figure 1). The Harmony Memory (HM) matrix is filled with HMS vectors as follows:

\[
\begin{bmatrix}
X_{11} & X_{12} & X_{13} & \cdots & X_{1G} \\
X_{21} & X_{22} & X_{23} & \cdots & X_{2G} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
X_{HMS1} & X_{HMS2} & X_{HMS3} & \cdots & X_{HMSG} \\
\end{bmatrix}_{HMS \times G}
\]

where \( x_i = x_{ij} \); \( i \in \{1, 2, 3, ..., HMS\} \) and \( j \in \{1, 2, 3, ..., G\} \)

Step-II: Harmony memory considering (HMC) rule

For this rule, a new random number \( r_i \) is generated within the range \([0,1]\).

If \( r_i < \text{HMC} \), then the first decision variable in the new vector \( x_{ij}^{\text{new}} \) is chosen randomly from the values in the current HM as follows:

\[
HM = \begin{bmatrix}
X_{11} & X_{12} & X_{13} & \cdots & X_{1G} \\
X_{21} & X_{22} & X_{23} & \cdots & X_{2G} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
X_{HMS1} & X_{HMS2} & X_{HMS3} & \cdots & X_{HMSG} \\
\end{bmatrix}_{HMS \times G}
\]
where HMCR is the Harmony Memory Consideration Rate (Figure 2).

\[ X_{ij}^{\text{New}} = X_{ij}; \quad X_{ij} \in \{X_{1j}, X_{2j}, X_{3j}, ..., X_{HMSj}\} \quad (19) \]

**Step-III: Pitch adjusting rate (PAR)**

The obtained decision variables from the harmony memory consideration rule is further examined to determine if it needs to pitch adjustment or not (Figure 3).

**Figure 3. Pitch adjustment rate.**

**Figure 4. Updation of worst harmony with best harmony.**

**Figure 5. Ensemble consideration.**

**Figure 6. Violated harmony consideration.**
Figure 7. Recursive search procedure for hybrid harmony search-random search algorithm.

Figure 8. Convergence of DE-random search algorithm for 4- and 10-generating unit test system. (a) 4-Unit test system (b) 10-Unit test system (SR = 10%) (c) 10-Unit test system (SR = 5%).

Figure 9. Variation of cost and emission w.r.t. weights for IEEE-14, 30 and 56-bus system.

Table 1. Committed status and generation scheduling of 4-unit test system

| Hour | U1 | U2 | U3 | U4 | U1 | U2 | U3 | U4 |
|------|----|----|----|----|----|----|----|----|
| 1    | 1  | 1  | 0  | 0  | 300| 150| 0  | 0  |
| 2    | 1  | 1  | 1  | 0  | 300| 205| 25 | 0  |
| 3    | 1  | 1  | 1  | 1  | 300| 250| 30 | 20 |
| 4    | 1  | 1  | 1  | 0  | 300| 215| 25 | 0  |
| 5    | 1  | 0  | 1  | 1  | 300| 0  | 80 | 20 |
| 6    | 1  | 0  | 1  | 0  | 255| 0  | 25 | 0  |
| 7    | 1  | 0  | 1  | 0  | 265| 0  | 25 | 0  |
| 8    | 1  | 1  | 0  | 0  | 300| 200| 0  | 0  |

Total cost ($) 74476.00
Time (Sec.) 22.863569
Table 2. Comparison of results for 4-generating unit system

| Method                                      | Generation cost ($) | Iteration time (sec.) |
|---------------------------------------------|---------------------|-----------------------|
|                                             | Best         | Average | Worst | Best | Average | Worst |
| Improved Lagrangian Relaxation (ILR)        | 75,231.9     | NA      | NA    | –    | –        | –     |
| (Sriyanyong & Song, 2005)                   |              |         |       |      |          |       |
| B. SMP (Khanmohammadi et al., 2010)         | 74,812       | 74,877  | 75,166| –    | –        | –     |
| A. SMP (Khanmohammadi et al., 2010)         | 74,812       | 74,877  | 75,166| –    | –        | –     |
| Lagrangian relaxation and PSO (LRPSO)        | 74,808       | NA      | NA    | –    | –        | –     |
| (Sriyanyong & Song, 2005)                   |              |         |       |      |          |       |
| Binary differential evolution (BDE)          | 74,676       | NA      | NA    | –    | –        | –     |
| (Jeong, Lee, Kim, Park, & Shin, 2009)        |              |         |       |      |          |       |
| Genetic algorithm (GA) (Valenzuela & Smith, 2002) | 74,675     | NA      | NA    | –    | –        | –     |
| HS and random search algorithm (Proposed algorithm) | 74,476     | 74,476  | 74,476| 20.68704 | 22.86357 | 22.9709 |

Table 3. Committed status of 10-unit test system (with 10% spinning reserve)

| Hour | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 |
|------|----|----|----|----|----|----|----|----|----|-----|
| 1    | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |
| 2    | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |
| 3    | 1  | 1  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0   |
| 4    | 1  | 1  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0   |
| 5    | 1  | 1  | 0  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 6    | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 7    | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 8    | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 9    | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0   |
| 10   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0   |
| 11   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0   |
| 12   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 1   |
| 13   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0   |
| 14   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0   |
| 15   | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 16   | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 17   | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 18   | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 19   | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0   |
| 20   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0   |
| 21   | 1  | 1  | 1  | 1  | 1  | 1  | 1  | 0  | 0  | 0   |
| 22   | 1  | 1  | 0  | 0  | 1  | 1  | 0  | 0  | 0  | 0   |
| 23   | 1  | 1  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0   |
| 24   | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |

Best generation cost($) = 563937.68748999
Best iteration time = 16.831236 Seconds
A new random vector \( r_2 \) is generated within the range [0,1].

If, then the pitch adjustment decision variable is calculated as follows:

where, PAR is Pitch Adjustment Rate.

Pitch Adjustment Rate:

\[
X_{\theta}^{\text{New}} = X_{\theta} + r \pm (0, 1) \times BW
\]  \hspace{1cm} (20)

where BW is a bandwidth factor, which is used to control the local search around the selected decision variable in the new vector.

**Step-IV: Random initialization rule**

If the condition \( r_1 < \text{HMCR} \) fails, the new first decision variable in the new vector \( X_{\theta}^{\text{New}} \) is generated randomly as follows:

### Table 4. Generation scheduling of 10-unit test system (for 10% spinning reserve)

| Hour | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 |
|------|----|----|----|----|----|----|----|----|----|-----|
| 1    | 455| 245| 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |
| 2    | 455| 295| 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |
| 3    | 455| 330| 0  | 0  | 25 | 0  | 0  | 0  | 0  | 0   |
| 4    | 455| 455| 0  | 0  | 40 | 0  | 0  | 0  | 0  | 0   |
| 5    | 455| 390| 0  | 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 6    | 455| 360| 130| 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 7    | 455| 410| 130| 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 8    | 455| 455| 130| 130| 30 | 0  | 0  | 0  | 0  | 0   |
| 9    | 455| 455| 130| 130| 85 | 20 | 25 | 0  | 0  | 0   |
| 10   | 455| 455| 130| 130| 162| 33 | 25 | 10 | 0  | 0   |
| 11   | 455| 455| 130| 130| 162| 73 | 25 | 10 | 0  | 0   |
| 12   | 455| 455| 130| 130| 162| 80 | 25 | 43 | 10 | 0   |
| 13   | 455| 455| 130| 130| 162| 33 | 25 | 10 | 0  | 0   |
| 14   | 455| 455| 130| 130| 85 | 20 | 25 | 0  | 0  | 0   |
| 15   | 455| 455| 130| 130| 30 | 0  | 0  | 0  | 0  | 0   |
| 16   | 455| 310| 130| 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 17   | 455| 260| 130| 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 18   | 455| 360| 130| 130| 25 | 0  | 0  | 0  | 0  | 0   |
| 19   | 455| 455| 130| 130| 30 | 0  | 0  | 0  | 0  | 0   |
| 20   | 455| 455| 130| 130| 162| 33 | 25 | 10 | 0  | 0   |
| 21   | 455| 455| 130| 130| 85 | 20 | 25 | 0  | 0  | 0   |
| 22   | 455| 455| 130| 130| 0  | 0  | 145| 20 | 25 | 0   |
| 23   | 455| 425| 0  | 0  | 0  | 20 | 0  | 0  | 0  | 0   |
| 24   | 455| 345| 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   |

Best generation cost ($) = 563937.68748999

Best iteration time = 16.831236 Seconds
Table 5. Comparison of results for 10-generating unit system (for 10% spinning reserve)

| S. No. | Method                                                                 | Overall generation cost ($) | Average time (sec.) |
|--------|------------------------------------------------------------------------|-----------------------------|---------------------|
| 1      | Genetic based method (Maifeld & Sheble, 1996)                         | NA                          | –                   |
| 2      | Hybrid continuous relaxation and genetic algorithm (CRGA) (Tokoro, Masuda, & Nishino, 2008) | NA                          | –                   |
| 3      | Continuous relaxation and genetic algorithm (CRGA) (Tokoro, Masuda, & Nishino, 2008) | –                           | 5,63,977            |
| 4      | Integer coded genetic algorithm (ICGA) (Damousis, Bakirtzis, & Dakopoulos, 2004) | –                           | 5,66,404            |
| 5      | Lagrangian Search Genetic Algorithm (LSGA) (Sheblé, Maifeld, Brittig, Fahd, & Fukurozaki-Coppinger, 1996) | 6,09,023.69                 | –                   |
| 6      | Improved binary particle swarm optimization (IBPSO) (Yuan et al., 2009) | 5,99,782                    | –                   |
| 7      | New genetic algorithm (Ganguly, Sarkar, & Pal, 2004)                   | 5,91,715                    | –                   |
| 8      | PSO (Grefenstette, 1986)                                              | 5,81,450                    | –                   |
| 9      | Binary Particle Swarm Optimization with bit Change Mutation (MPSO) (Lee, Park, & Jeon, 2007) | 5,74,905                    | –                   |
| 10     | HPSO (Gaing, 2003d)                                                    | 5,74,153                    | –                   |
| 11     | LCA-PSO (Wang, Li, & Watada, 2011)                                     | 5,70,006                    | –                   |
| 12     | Two-Stage Genetic Based Technique (TSGA) (Eladin, Elsayed, & Youssef, 2008) | 5,68,315                    | –                   |
| 13     | Hybrid PSO-SQP (Victoire & Jeyakumar, 2004)                             | 5,68,032.3                  | –                   |
| 14     | BCGA (Damousis et al., 2004)                                           | 5,67,367                    | –                   |
| 15     | SM (Simopoulos, Kavatza, & Vournas, 2006b)                              | 5,66,686                    | 5,66,787            |
| 16     | LR (Simopoulos et al., 2006b)                                          | 5,66,107                    | 5,66,493            |
| 17     | GA (Simopoulos et al., 2006b)                                          | 5,65,866                    | 5,67,329            |
| 18     | Genetic Algorithm (GA) (Kazarlis et al., 1996)                         | 5,65,852                    | –                   |
| 19     | Enhanced Simulated Annealing (ESA) (Simopoulos, Kavatza, & Vournas, 2006b) | 5,65,828                    | 5,65,988            |
| 20     | Lagrangian Relaxation (LR) (Kazarlis et al., 1996)                     | 5,65,825                    | –                   |
| 21     | Dynamic Programming (DP) (Kazarlis et al., 1996)                       | 5,65,825                    | –                   |
| 22     | Improved Lagrangian Relaxation (ILR) (Sriyanyong & Song, 2005)        | 5,65,823.23                 | –                   |
| 23     | LRPSO (Sriyanyong & Song, 2005)                                        | 5,65,275.2                  | –                   |
| 24     | Lagrangian Relaxation and Genetic Algorithm (LRGA) (Cheng, Liu, & Liu, 2000d) | 5,64,800                    | –                   |
| 25     | Evolutionary Programming (EP) (Juste, Kita, Tanaka, & Hasegawa, 1999)  | 5,64,551                    | 5,65,352            |
| 26     | EP (Simopoulos et al., 2006b)                                          | 5,64,551                    | 5,65,352            |
| 27     | Particle Swarm Optimization (PSO) (Zhao, Gua, Bai, & Cao, 2006)        | 5,64,212                    | 5,65,103            |
| 28     | Ant Colony Search Algorithm (ACSA) (Sum-im & Ongsakul, 2003)           | 5,64,049                    | –                   |
| 29     | Hybrid Ant System/Priority List (HASP) (Chusanappittut, Nuadhoong, Jantarang, & Phoomvuthisarn, 2008) | 5,64,029                    | 5,64,324            |
| 30     | B. SMP (Khanmohammadi et al., 2010)                                    | 5,64,017.73                 | 5,64,121.46         |

(Continued)
where $P_{minij}$, $P_{maxij}$ are the lower and upper bounds for generating units and $r$ and $(0, 1)$ is the random vector within the range $[0,1]$.

Step-V: Harmony memory updating

$$X_{ij}^{new} = P_{minij} + (P_{maxij} - P_{minij}) \cdot r$$

Table 5. (Continued)

| S. No. | Method                                                                 | Overall generation cost ($) | Average time (sec.) |
|--------|------------------------------------------------------------------------|----------------------------|---------------------|
| 31     | Annealing Genetic Algorithm (AGA) (Cheng, Liu, & Liu, 2000b)           | 5,64,005                   |                     |
| 32     | Binary Differential Evolution (Jeong, Lee, et al., 2009)               | 5,63,997                   |                     |
| 33     | Social Evolutionary Programming (SEP) (Wang, Y., & Zhang, 2004)         | 5,63,987                   |                     |
| 34     | Methodological Priority List (MPL) (Tingfang & Ting, 2008)             | 5,63,977.1                 |                     |
| 35     | Genetic Algorithm (GA) (Kazarlis et al., 1996)                        | 5,63,977                   | 56,65,606           |
| 36     | IBPSO (Yuan et al., 2009)                                             | 5,63,977                   | 56,155              |
| 37     | Genetic Algorithm Based on Unit Characteristics (UCC-GA) (Senjyu, Yamashiro, Uezato, & Funabashi, 2002) | 5,63,977                   |                     |
| 38     | Enhanced Adaptive Lagrangian Relaxation (EALR) (Ongsakul & Petcharaks, 2004) | 5,63,977                   | 56,65,606           |
| 39     | Local Search Method (LCM) (Fei & Jinghua, 2009)                       | 5,63,977                   |                     |
| 40     | Quantum-Inspired Binary PSO (QBPSO) (Jeong, Park, Jang, & Lee, 2010)  | 5,63,977                   |                     |
| 41     | Binary PSO (Jeong, Park, et al., 2009)                                | 5,63,977                   |                     |
| 42     | Quantum-Inspired Binary PSO (QIBPSO) (Jeong, Park, et al., 2009)      | 5,63,977                   |                     |
| 43     | Extended Priority List (EPL) (Senju et al., 2003)                     | 5,63,977                   |                     |
| 44     | Muller Method (Chandram, Subrahmanyam, & Sydulu, 2011)                 | 5,63,977                   |                     |
| 45     | Improved Particle Swarm Optimization (IPSO) (Zhao et al., 2006)        | 5,63,954                   | 56,162              |
| 46     | Advanced Fuzzy Controlled Binary PSO (AFBPSO) (Chakraborty, Ito, Senju, & Saber, 2012) | 5,63,947                   | 56,128              |
| 47     | Hybrid PSO (HPSO) (Ting, Rao, & Lao, 2006)                            | 5,63,947                   | 56,477              |
| 48     | Fuzzy Quantum Computation Based Thermal Unit Commitment (FQEA) (Chakraborty, Senju, Yona, & Funabashi, 2011) | 5,63,942                   |                     |
| 49     | Advanced Quantum-Inspired Evolutionary Algorithm (AQEA) (Chung, Yu, & Wong, 2006) | 5,63,938                   |                     |
| 50     | Particle Swarm-Based- Simulated Annealing (PSO-B-SA) (Sadati, Hajian, & Zamani, 2007) | 5,63,938                   | 56,411              |
| 51     | QEA-UC (Chung et al., 2006)                                           | 5,63,938                   | 56,4012             |
| 52     | IGEA-UC (Chung et al., 2006)                                          | 5,63,938                   | 56,3938             |
| 53     | Gravitational Search Algorithm (Ray, 2013)                             | 5,63,938                   | 56,6008             |
| 54     | A-SMP (Khanmohammadi et al., 2010)                                    | 5,63,937.26                | 56,4040.3           |
| 55     | Harmony Search (HS) (Najafi & pourjamal, 2012)                          | 5,64,367.69                |                     |
| 56     | Harmony Search Algorithm (HAS) (Afkousi-Paqaleh & Rashidinejad, 2010) | 5,63,977                   | 56,168.6            |
| 57     | HS- Random Search [Proposed Algorithm]                                | 5,63,937.6875              | 56,965.31           | 56,995.33           | 16.831236

$$X_{ij}^{new} = P_{minij} + (P_{maxij} - P_{minij}) \cdot r$$ and $(0, 1)$
After the Harmony Vector $X_{ij}^{new}$ is generated, it will replace the worst harmony vector $X_{ij}^{Worst}$ in the Harmony memory if its objective function value is better than the objective function value of the worst harmony vector (Figure 4). PSEUDO code for updation of Worst Harmony Vector (WHV) with new random harmony vector is mentioned below.

\[
\text{If } \left( X_{ij}^{new} < X_{ij}^{Worst} \right) \text{ then} \\
\text{Update the HM as } X_{ij}^{Worst} = X_{ij}^{new} \\
\text{end if}
\]

**Step-VI: Ensemble consideration**

After the new harmony $X_{ij}^{new} = X_{ij}^*; X_j \in \{ X_{1j}, X_{2j}, X_{3j}, ..., X_{HMSj} \}$ is obtained, one more operation can be considered from the relationship among decision variables. Just as a player has even stronger relationship with specific player in a music group, the new operation, ensemble consideration (Geem, 2006b), enables the algorithm to combine closely related variables together.

**Step-VII: Violated harmony consideration**

Once the new harmony is obtained using the above-mentioned rules, it is then checked whether it violates problem constraints. Although the new harmony violates the constraints, it has still
chance to be included in HM, just as rule-violated harmony was still used by musicians such as famous composer Ludwig van Beethoven (Geem, 2006b). Violated harmony can be considered by adding a penalty (Figures 5 and 6). The suitable penalty can be mathematically described as:

\[
\text{Penalty} = a \times (\text{ViolationAmount})^b \times c
\]  \hspace{1cm} (22)

- **Randomization in harmony search algorithm**

Randomization in Harmony Search algorithm is to increase the diversity of the solutions. Although the pitch adjustment has a similar role, it is limited to certain area and thus corresponds to a local search. The use of randomization can drive the system further to explore various diverse solutions so as to attain the global optimality. The Pseudo code of Proposed Algorithm (Figure 7), the probability of randomization is

| Hour | U1   | U2   | U3   | U4   | U5   | U6   | U7   | U8   | U9   | U10  |
|------|------|------|------|------|------|------|------|------|------|------|
| 1    | 455  | 245  | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
| 2    | 455  | 295  | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
| 3    | 455  | 395  | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
| 4    | 455  | 455  | 0    | 0    | 40   | 0    | 0    | 0    | 0    | 0    |
| 5    | 455  | 455  | 0    | 0    | 90   | 0    | 0    | 0    | 0    | 0    |
| 6    | 455  | 455  | 130  | 0    | 60   | 0    | 0    | 0    | 0    | 0    |
| 7    | 455  | 410  | 130  | 130  | 25   | 0    | 0    | 0    | 0    | 0    |
| 8    | 455  | 455  | 130  | 130  | 30   | 0    | 0    | 0    | 0    | 0    |
| 9    | 455  | 455  | 130  | 130  | 105  | 0    | 25   | 0    | 0    | 0    |
| 10   | 455  | 455  | 130  | 130  | 162  | 43   | 25   | 0    | 0    | 0    |
| 11   | 455  | 455  | 130  | 130  | 162  | 80   | 28   | 0    | 0    | 10   |
| 12   | 455  | 455  | 130  | 130  | 162  | 43   | 25   | 0    | 0    | 0    |
| 13   | 455  | 455  | 130  | 130  | 130  | 105  | 25   | 0    | 0    | 0    |
| 14   | 455  | 455  | 130  | 130  | 130  | 110  | 20   | 0    | 0    | 0    |
| 15   | 455  | 455  | 130  | 130  | 0    | 140  | 20   | 0    | 0    | 0    |
| 16   | 455  | 440  | 130  | 0    | 25   | 0    | 0    | 0    | 0    | 0    |
| 17   | 455  | 390  | 130  | 0    | 25   | 0    | 0    | 0    | 0    | 0    |
| 18   | 455  | 455  | 130  | 0    | 60   | 0    | 0    | 0    | 0    | 0    |
| 19   | 455  | 455  | 130  | 0    | 135  | 0    | 25   | 0    | 0    | 0    |
| 20   | 455  | 455  | 130  | 130  | 130  | 25   | 0    | 0    | 0    | 0    |
| 21   | 455  | 455  | 130  | 130  | 105  | 0    | 25   | 0    | 43   | 0    |
| 22   | 455  | 385  | 130  | 130  | 130  | 0    | 0    | 0    | 0    | 0    |
| 23   | 455  | 315  | 0    | 130  | 0    | 0    | 0    | 0    | 0    | 0    |
| 24   | 455  | 215  | 0    | 130  | 0    | 0    | 0    | 0    | 0    | 0    |
and the actual probability of the pitch adjustment is

\[ P_{\text{Pitch}} = r_{\text{accept}} \times r_{\text{pa}} \]  

where \( r_{\text{accept}} \) is the Harmony memory accepting rate and \( r_{\text{pa}} \) represents the Pitch Adjustment rate.

### Table 8. Comparison of results for 10-generating unit system (for 5% spinning reserve)

| Method                  | Overall generation cost ($) |
|-------------------------|----------------------------|
|                         | Best cost ($) | Average cost ($) | Worst cost ($) |
| BPSO (Gaing, 2003c)     | 5,65,804      | 5,66,992         | 5,67,251       |
| GA (Gaing, 2003c)       | 5,70,781      | 5,74,280         | 5,76,791       |
| APSO (Pappala & Erlich, 2008) | 5,61,586   | -                | -              |
| BP (Pappala & Erlich, 2008) | 5,65,450     | -                | -              |
| TSGB (Eldin et al., 2008) | 5,60,263.92  | -                | -              |
| IPSO (Xiong, Li, & Cheng, 2008) | 5,58,114.80 | -                | -              |
| Hybrid PSO-SQP (Victoire & Jeyakumar, 2004) | 5,68,032.30 | -                | -              |
| B.SMP (Khanmohammadi et al., 2010) | 5,58,844.76 | 5,55,937.24     | 5,59,154.98   |
| HS-Random Search        | 5,57,905.6427| 5,58,267.2       | 5,58,682.0107 |

### Table 9. Conclusion of results for 4- and 10-units test system

| No. of units | Generation cost ($) | Computational time (sec) |
|--------------|---------------------|--------------------------|
|              | Best cost | Average cost | Worst cost | Best time | Average time | Worst time |
| 4            | 74,476     | 74,476       | 74,476     | 20.68704  | 22.863569   | 22.9709    |
| 10 (SR = 10%)| 5,63,937   | 5,63,965.3094| 5,63,995.3262 | 16.831236 | 16.9158306  | 16.99832   |
| 10 (SR = 5%) | 5,57,905.6427| 5,58,267.2   | 5,58,682.0107| 14.36105  | 15.88731    | 16.33696   |

### Table 10. Comparison of proposed algorithm with other harmony search algorithms

| Method                                        | 10-unit system | 20-units system | 40-units system |
|-----------------------------------------------|----------------|-----------------|-----------------|
|                                               | Best cost | Mean cost | Worst cost | Execution time | Best cost | Execution time | Best cost | Execution time |
| Harmony Search (Najafi & pourjamal, 2012)      | 5,64,367.69| -        | -         | -              | 11,27,377 | 92              | 2,25,0968 | 467            |
| Harmony Search Algorithm (HAS) (Afkousi-Paqaleh & Rashidinejad, 2010) | 5,63,977 | 5,64,168.6 | -         | 3.00           | 11,24,715 | 24              | 22,48,740 | 78             |
| Proposed Method                               | 5,63,937.69| 5,63,965.31| 5,63,995.3262 | 16.831236 | 11,24,912.84 | 35.01579 | 22,48,653 | 179.66679     |
### Table 11. Commitment and generation schedule for 14–bus system

| Commitment schedule | Generation schedule |
|---------------------|---------------------|
| Hour | U1 | U2 | U3 | U4 | U5 | U1 | U2 | U3 | U4 | U5 |
| 1 | 1 | 0 | 0 | 0 | 0 | 148 | 0 | 0 | 0 | 0 |
| 2 | 1 | 0 | 0 | 0 | 0 | 173 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 0 | 0 | 0 | 220 | 0 | 0 | 0 | 0 |
| 4 | 1 | 1 | 0 | 0 | 0 | 104 | 140 | 0 | 0 | 0 |
| 5 | 1 | 1 | 0 | 0 | 0 | 119 | 140 | 0 | 0 | 0 |
| 6 | 1 | 1 | 0 | 0 | 0 | 108 | 140 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 0 | 227 | 0 | 0 | 0 | 0 |
| 8 | 1 | 0 | 0 | 0 | 0 | 202 | 0 | 0 | 0 | 0 |
| 9 | 1 | 0 | 0 | 0 | 0 | 176 | 0 | 0 | 0 | 0 |
| 10 | 1 | 0 | 0 | 0 | 0 | 134 | 0 | 0 | 0 | 0 |
| 11 | 1 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 |
| 12 | 1 | 0 | 0 | 0 | 0 | 130 | 0 | 0 | 0 | 0 |
| 13 | 1 | 0 | 0 | 0 | 0 | 157 | 0 | 0 | 0 | 0 |
| 14 | 1 | 0 | 0 | 0 | 0 | 168 | 0 | 0 | 0 | 0 |
| 15 | 1 | 0 | 0 | 0 | 0 | 195 | 0 | 0 | 0 | 0 |
| 16 | 1 | 0 | 0 | 0 | 0 | 225 | 0 | 0 | 0 | 0 |
| 17 | 1 | 1 | 0 | 0 | 0 | 104 | 140 | 0 | 0 | 0 |
| 18 | 1 | 1 | 0 | 0 | 0 | 101 | 140 | 0 | 0 | 0 |
| 19 | 1 | 1 | 0 | 0 | 0 | 90 | 140 | 0 | 0 | 0 |
| 20 | 1 | 0 | 0 | 0 | 0 | 210 | 0 | 0 | 0 | 0 |
| 21 | 1 | 0 | 0 | 0 | 0 | 176 | 0 | 0 | 0 | 0 |
| 22 | 1 | 0 | 0 | 0 | 0 | 157 | 0 | 0 | 0 | 0 |
| 23 | 1 | 0 | 0 | 0 | 0 | 138 | 0 | 0 | 0 | 0 |
| 24 | 1 | 0 | 0 | 0 | 0 | 103 | 0 | 0 | 0 | 0 |

#### 4.2. Flow chart of proposed algorithm

In order to obtain the hybrid version of Harmony search–Random search algorithm, the general operators of harmony search algorithm and random search algorithm are integrated recursively. The flow chart of Harmony search algorithm and PSEUDO code for random search algorithm is shown in Figure 7.

#### 4.3. Test systems

The simulation includes runs for IEEE-14 Bus, IEEE-30 Bus, IEEE-56 bus, 4-units and 10-units test systems. Scheduling periods are 8 h for 4-units test system and 24-h IEEE-14 bus, IEEE-30 bus, IEEE-56 bus and 10-units test system. The generating units characteristics and load demand data for 4-units test system are taken from Khanmohammadi, Amiri, and Haque (2010) and are shown in Tables 14 and 15, respectively. The characteristics of 10-units test system are taken from Khanmohammadi et al. (2010) and are shown in Table 16 and load demand pattern is shown in Table 17. The generating units characteristics along with emission coefficients and load demand for IEEE-14 Bus, IEEE-30 bus and IEEE 56-bus test systems are shown in Tables 18–26.
The corresponding results have been obtained using hybrid harmony search algorithm using population size of 40 and number of searches from 150 to 1,000 for 4- and 10-units test system. For multi-objective UCP, IEEE-14, 30 and 56 bus system is tested for number of searches of 30 and taking number of pareto 50. The recursive search procedure for proposed hybrid harmony search-random search algorithm is shown in Figure 7. The performance of the proposed algorithm is tested in MATLAB 2013a (8.1.0.604) software on Intel® core™ i-5–3470S CPU@ 2.90 GHz, 4.00 GB RAM system.

### 4.4. Results and discussion

In order to stochastic nature of Hybrid HS-random Search algorithm, 50 test trials were made for each problem set, with each run starting with different initial populations. The Population size of 40 (for 4- and 10-units test system) was taken in all runs (Figure 8). The simulation results are shown in Table 1 through and Figure 9. As shown in comparison, Table 2 for 4-units test system, Table 5 for 10-Units test system with 10% spinning reserve, Table 8 for 10-Units test system with 5% spinning reserve shows that proposed hybrid Harmony Search-Random Search algorithm gives better solution in comparison with other well-known meta-heuristics algorithms. In comparison with the results produced by reported methods, the proposed method gives satisfactory solution in reasonable

| Table 12. Commitment and generation schedule for 30-bus system |
| --- |
| Commitment schedule | Generation schedule |
| Hour | U1 | U2 | U3 | U4 | U5 | U6 | U1 | U2 | U3 | U4 | U5 | U6 |
| 1 | 0 | 1 | 50 | 0 | 0 | 1 | 0 | 80 | 50 | 0 | 0 | 18 |
| 2 | 1 | 1 | 0 | 0 | 0 | 0 | 93 | 80 | 0 | 0 | 0 | 0 |
| 3 | 1 | 1 | 0 | 0 | 0 | 0 | 140 | 80 | 0 | 0 | 0 | 0 |
| 4 | 1 | 1 | 0 | 0 | 0 | 0 | 164 | 80 | 0 | 0 | 0 | 0 |
| 5 | 1 | 1 | 1 | 0 | 0 | 0 | 129 | 80 | 50 | 0 | 0 | 0 |
| 6 | 1 | 1 | 0 | 0 | 0 | 0 | 168 | 80 | 0 | 0 | 0 | 0 |
| 7 | 1 | 1 | 0 | 0 | 0 | 0 | 147 | 80 | 0 | 0 | 0 | 0 |
| 8 | 1 | 1 | 0 | 0 | 0 | 0 | 122 | 80 | 0 | 0 | 0 | 0 |
| 9 | 1 | 0 | 0 | 0 | 0 | 0 | 176 | 0 | 0 | 0 | 0 | 0 |
| 10 | 1 | 0 | 0 | 0 | 0 | 0 | 134 | 0 | 0 | 0 | 0 | 0 |
| 11 | 1 | 0 | 0 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 |
| 12 | 1 | 0 | 0 | 0 | 0 | 0 | 130 | 0 | 0 | 0 | 0 | 0 |
| 13 | 1 | 0 | 0 | 0 | 0 | 0 | 157 | 0 | 0 | 0 | 0 | 0 |
| 14 | 1 | 0 | 0 | 0 | 0 | 0 | 168 | 0 | 0 | 0 | 0 | 0 |
| 15 | 1 | 1 | 0 | 0 | 0 | 0 | 115 | 80 | 0 | 0 | 0 | 0 |
| 16 | 1 | 1 | 0 | 0 | 0 | 0 | 145 | 80 | 0 | 0 | 0 | 0 |
| 17 | 1 | 1 | 0 | 0 | 0 | 0 | 164 | 80 | 0 | 0 | 0 | 0 |
| 18 | 1 | 1 | 0 | 0 | 0 | 0 | 161 | 80 | 0 | 0 | 0 | 0 |
| 19 | 1 | 1 | 0 | 0 | 0 | 0 | 150 | 80 | 0 | 0 | 0 | 0 |
| 20 | 1 | 1 | 0 | 0 | 0 | 0 | 130 | 80 | 0 | 0 | 0 | 0 |
| 21 | 1 | 0 | 0 | 0 | 0 | 0 | 176 | 0 | 0 | 0 | 0 | 0 |
| 22 | 1 | 0 | 0 | 0 | 0 | 0 | 157 | 0 | 0 | 0 | 0 | 0 |
| 23 | 1 | 0 | 0 | 0 | 0 | 0 | 138 | 0 | 0 | 0 | 0 | 0 |
| 24 | 1 | 0 | 0 | 0 | 0 | 0 | 103 | 0 | 0 | 0 | 0 | 0 |
Table 13. Commitment and generation schedule for 56-bus system

| Commitment schedule | Generation schedule |
|---------------------|---------------------|
| Hour | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U1 | U2 | U3 | U4 | U5 | U6 | U7 |
| 1    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 148| 0  | 0  | 0  | 0  | 0  | 0  |
| 2    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 173| 0  | 0  | 0  | 0  | 0  | 0  |
| 3    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 220| 0  | 0  | 0  | 0  | 0  | 0  |
| 4    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 244| 0  | 0  | 0  | 0  | 0  | 0  |
| 5    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 259| 0  | 0  | 0  | 0  | 0  | 0  |
| 6    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 248| 0  | 0  | 0  | 0  | 0  | 0  |
| 7    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 227| 0  | 0  | 0  | 0  | 0  | 0  |
| 8    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 202| 0  | 0  | 0  | 0  | 0  | 0  |
| 9    | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 176| 0  | 0  | 0  | 0  | 0  | 0  |
| 10   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 134| 0  | 0  | 0  | 0  | 0  | 0  |
| 11   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 100| 0  | 0  | 0  | 0  | 0  | 0  |
| 12   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 130| 0  | 0  | 0  | 0  | 0  | 0  |
| 13   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 157| 0  | 0  | 0  | 0  | 0  | 0  |
| 14   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 168| 0  | 0  | 0  | 0  | 0  | 0  |
| 15   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 195| 0  | 0  | 0  | 0  | 0  | 0  |
| 16   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 225| 0  | 0  | 0  | 0  | 0  | 0  |
| 17   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 244| 0  | 0  | 0  | 0  | 0  | 0  |
| 18   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 241| 0  | 0  | 0  | 0  | 0  | 0  |
| 19   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 230| 0  | 0  | 0  | 0  | 0  | 0  |
| 20   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 210| 0  | 0  | 0  | 0  | 0  | 0  |
| 21   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 176| 0  | 0  | 0  | 0  | 0  | 0  |
| 22   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 157| 0  | 0  | 0  | 0  | 0  | 0  |
| 23   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 138| 0  | 0  | 0  | 0  | 0  | 0  |
| 24   | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 103| 0  | 0  | 0  | 0  | 0  | 0  |

Computation time (Tables 9 and 10). Table 1 gives commitment and generation schedule for 4-units test system (Total Cost: $74476). Tables 3 and 4 give commitment and generation schedule for 10-units test system with 10% spinning reserve (Total Cost: $563937.6875). Tables 6 and 7 give commitment and generation schedule for 10-units test system with 5% spinning reserve (Total Cost: $557905.6427). The test data for IEEE-14, 30 and 56-bus systems along with load demand of 24-h are shown in Tables 14–17 and Commitment and generation schedule for IEEE-14, 30 and 56-bus system for multi-objective optimization are shown in Tables 11–13, respectively, and Figure 9 shows the variation of Cost and Emission w.r.t. weights for IEEE-14, 30 and 56-Bus systems.

5. Conclusion and future scope

In this paper, researchers have presented the solution of multi-objective UCP using Hybrid Harmony Search-Random Search Algorithm. The results for standard IEEE-14, 30 and 56-bus systems have been successfully evaluated for multi-objective UCP and the test systems consisting of 4 and 10 units are tested for single-objective evaluation using proposed hybrid algorithm. It has been observed that performance of proposed Hybrid algorithm is much better than other well-known and recently developed evolutionary, heuristics and meta-heuristics search algorithm. For Multi-Objective criterion, it has been found that as there is a conflicting relationship between cost and emission, if the performance in cost criterion is improved, performance in the emission is seen to deteriorate. Thus, to achieve best compromising solution with respect to cost and emission, suitable adjustment in weights is required.
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### Table 14. Four-unit test system (Khanmohammadi et al., 2010)

| Unit No. | $p_{\text{max}}^\text{ih}$ | $p_{\text{min}}^\text{ih}$ | $\alpha$ ($$/\text{MW}^2 \text{ h}$$) | $\beta$ ($$/\text{MWh}$$) | $\gamma$ ($$/\text{h}$$) | MUT$_i$ | MDT$_i$ | HSC$_i$ | CSC$_i$ | CSH$_i$ | IS$_i$ |
|----------|-----------------|-----------------|-----------------|-----------------|-----------------|-------|-------|-------|-------|-------|-------|
| U1       | 300             | 75              | 684.74          | 16.83           | 0.0021          | 5     | 4     | 500   | 1100  | 5     | 8     |
| U2       | 250             | 60              | 585.62          | 16.95           | 0.0042          | 5     | 3     | 170   | 400   | 5     | 8     |
| U3       | 80              | 25              | 213             | 20.74           | 0.0018          | 4     | 2     | 150   | 350   | 4     | −5    |
| U4       | 60              | 20              | 252             | 23.6            | 0.0034          | 1     | 1     | 0     | 0.02  | 0     | −6    |

### Table 15. Load demand for four-unit test system

| Hour | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  |
|------|----|----|----|----|----|----|----|----|
| Load demand | 450 | 530 | 600 | 540 | 400 | 280 | 290 | 500 |

### Table 16. Test data for 10-unit system (Khanmohammadi et al., 2010)

| Unit No. | $p_{\text{max}}^\text{ih}$ | $p_{\text{min}}^\text{ih}$ | $\alpha$ ($$/\text{MW}^2 \text{ h}$$) | $\beta$ ($$/\text{MWh}$$) | $\gamma$ ($$/\text{h}$$) | MUT$_i$ | MDT$_i$ | HSC$_i$ | CSC$_i$ | CSH$_i$ | IS$_i$ |
|----------|-----------------|-----------------|-----------------|-----------------|-----------------|-------|-------|-------|-------|-------|-------|
| U1       | 455             | 150             | 1,000           | 16.19           | 0.00048         | 8     | 8     | 4,500 | 9,000 | 5     | 8     |
| U2       | 455             | 150             | 970             | 17.26           | 0.00031         | 8     | 8     | 5,000 | 10,000 | 5     | 8     |
| U3       | 130             | 20              | 700             | 16.6            | 0.002           | 5     | 5     | 550   | 1,100 | 4     | −5    |
| U4       | 130             | 20              | 680             | 16.5            | 0.00211         | 5     | 5     | 560   | 1,120 | 4     | −5    |
| U5       | 162             | 25              | 450             | 19.7            | 0.00398         | 6     | 6     | 900   | 1,800 | 4     | −6    |
| U6       | 80              | 20              | 370             | 22.26           | 0.00712         | 3     | 3     | 170   | 340   | 2     | −3    |
| U7       | 85              | 25              | 480             | 27.74           | 0.000799        | 3     | 3     | 260   | 520   | 2     | −3    |
| U8       | 55              | 10              | 660             | 25.92           | 0.00413         | 1     | 1     | 30    | 60    | 0     | −1    |
| U9       | 55              | 10              | 665             | 27.27           | 0.00222         | 1     | 1     | 30    | 60    | 0     | −1    |
| U10      | 55              | 10              | 670             | 27.79           | 0.00173         | 1     | 1     | 30    | 60    | 0     | −1    |
Table 17. Load demand pattern for 24 h for 10-unit system

| Hour | Demand |
|------|--------|
| 1    | 700    |
| 2    | 750    |
| 3    | 850    |
| 4    | 950    |
| 5    | 1,000  |
| 6    | 1,100  |
| 7    | 1,150  |
| 8    | 1,200  |
| 9    | 1,300  |
| 10   | 1,400  |
| 11   | 1,450  |
| 12   | 1,500  |
| 13   | 1,400  |
| 14   | 1,300  |
| 15   | 1,200  |
| 16   | 1,050  |
| 17   | 1,000  |
| 18   | 1,100  |
| 19   | 1,200  |
| 20   | 1,400  |
| 21   | 1,300  |
| 22   | 1,100  |
| 23   | 900    |
| 24   | 800    |

Table 18. Test data for IEEE 14-Bus System

| Unit No. | $P_{\text{max}}$ | $P_{\text{min}}$ | Minimum up-down time | Start-up costs | CSH_i | IS_i |
|----------|------------------|------------------|----------------------|----------------|-------|------|
|          | $P_{\text{max}}$ | $P_{\text{min}}$ | MUT_i, MDT_i, HSC_i, CSC_i |                |       |      |
| U1       | 250              | 10               | 1, 1                  | 70, 176        | 2     | 1    |
| U2       | 140              | 20               | 2, 1                  | 74, 187        | 2     | 3    |
| U3       | 100              | 15               | 1, 1                  | 50, 113        | 1     | 2    |
| U4       | 120              | 10               | 1, 2                  | 110, 267       | 1     | 3    |
| U5       | 45               | 10               | 1, 1                  | 72, 180        | 1     | -2   |
Table 19. Emission and fuel cost coefficients for IEEE 14–bus system

| Unit No. | Fuel cost coefficients | Emission coefficients |
|----------|------------------------|-----------------------|
|          | $a$ ($/MW^2$) | $b$ ($$/MWh$) | $c$ ($$/h$) | $\alpha$ | $\beta$ | $\gamma$ |
| U1       | 0.00375     | 2.00          | 0           | 22.983  | −0.90  | 0.0126   |
| U2       | 0.01750     | 1.75          | 0           | 25.313  | −0.10  | 0.0200   |
| U3       | 0.06250     | 1.00          | 0           | 25.505  | −0.01  | 0.0270   |
| U4       | 0.00834     | 3.25          | 0           | 24.900  | −0.005 | 0.0291   |
| U5       | 0.02500     | 3.00          | 0           | 24.700  | −0.004 | 0.0290   |

Table 20. Load demand for 24 h

| Hour | Demand |
|------|--------|
| 1    | 148    |
| 2    | 173    |
| 3    | 220    |
| 4    | 244    |
| 5    | 259    |
| 6    | 248    |
| 7    | 227    |
| 8    | 202    |
| 9    | 176    |
| 10   | 134    |
| 11   | 100    |
| 12   | 130    |
| 13   | 157    |
| 14   | 168    |
| 15   | 195    |
| 16   | 225    |
| 17   | 244    |
| 18   | 241    |
| 19   | 230    |
| 20   | 210    |
| 21   | 176    |
| 22   | 157    |
| 23   | 138    |
| 24   | 103    |

Table 21. Test data for IEEE 30-bus system

| Unit No. | $P_{\text{max}}$ | $P_{\text{min}}$ | $P_{\text{min}}$ | Minimum up-down time | Start-up cost | CSH$_i$ | IS$_i$ |
|----------|------------------|------------------|------------------|----------------------|---------------|---------|--------|
|          | $P_{\text{max}}$ | $P_{\text{min}}$ | $P_{\text{min}}$ | MUT$_i$   | MDT$_i$ | HSC$_i$ | CSC$_i$ |         |         |
| U1       | 200              | 50               | 2                | 1          | 1      | 70     | 176    | 2       | −1       |
| U2       | 80               | 20               | 2                | 2          | 2      | 74     | 187    | 1       | −3       |
| U3       | 50               | 15               | 2                | 1          | 1      | 50     | 113    | 1       | 2        |
| U4       | 35               | 10               | 2                | 1          | 2      | 110    | 267    | 1       | 3        |
| U5       | 30               | 10               | 2                | 1          | 1      | 72     | 180    | 1       | −2       |
| U6       | 40               | 12               | 2                | 1          | 1      | 40     | 113    | 1       | 2        |
### Table 22. Emission and fuel cost coefficients for IEEE 30-bus system

| Unit No. | Fuel cost coefficients | Emission coefficients |
|----------|------------------------|-----------------------|
|          | $a$ ($/MW^2$) | $b$ ($/MWh$) | $c$ ($$/h$) | $\alpha$ | $\beta$ | $\gamma$ |
| U1       | 0.00375       | 2               | 0          | 22.983  | −0.9   | 0.0126   |
| U2       | 0.0175        | 1.75            | 0          | 25.313  | −0.1   | 0.02     |
| U3       | 0.0625        | 1               | 0          | 25.505  | −0.01  | 0.027    |
| U4       | 0.00834       | 3.25            | 0          | 24.9    | −0.005 | 0.0291   |
| U5       | 0.025         | 3               | 0          | 24.7    | −0.004 | 0.029    |
| U6       | 0.025         | 3               | 0          | 25.3    | −0.0055| 0.0271   |

### Table 23. Load demand for 24 h

| Hour | Demand |
|------|--------|
| 1    | 148    |
| 2    | 173    |
| 3    | 220    |
| 4    | 244    |
| 5    | 259    |
| 6    | 248    |
| 7    | 227    |
| 8    | 202    |
| 9    | 176    |
| 10   | 134    |
| 11   | 100    |
| 12   | 130    |
| 13   | 157    |
| 14   | 168    |
| 15   | 195    |
| 16   | 225    |
| 17   | 244    |
| 18   | 241    |
| 19   | 230    |
| 20   | 210    |
| 21   | 176    |
| 22   | 157    |
| 23   | 138    |
| 24   | 103    |
### Table 24. Test data for IEEE 56-Bus System

| Unit No. | $P_{\text{max}}$ | $P_{\text{min}}$ | Minimum up-down time | Start-up cost | $C_{\text{SH}i}$ | $C_{\text{SI}i}$ |
|----------|------------------|------------------|----------------------|---------------|------------------|------------------|
| U1       | 576              | 50               | 3                    | 70            | 176              | 3                |
| U2       | 100              | 10               | 3                    | 74            | 187              | 2                |
| U3       | 140              | 20               | 2                    | 50            | 113              | 3                |
| U4       | 100              | 10               | 4                    | 110           | 267              | 1                |
| U5       | 550              | 40               | 1                    | 72            | 180              | 1                |
| U6       | 100              | 10               | 1                    | 40            | 113              | 1                |
| U7       | 410              | 30               | 2                    | 70            | 176              | 2                |

### Table 25. Emission and fuel cost coefficients for IEEE 57-bus system

| Unit No. | Fuel cost coefficients | Emission coefficients |
|----------|------------------------|-----------------------|
|          | $a$ ($$/\text{MW}^2$) | $b$ ($$/\text{MWh}$) | $c$ ($$/\text{h}$) | $\alpha$ | $\beta$ | $\gamma$ |
| U1       | 0.0017                 | 1.7365                | 0                   | 22.983   | -0.9   | 0.0126   |
| U2       | 0.01                   | 10                    | 0                   | 26.313   | -0.1   | 0.021    |
| U3       | 0.0071                 | 7.1429                | 0                   | 25.888   | -0.2   | 0.0194   |
| U4       | 0.01                   | 10                    | 0                   | 26.313   | -0.1   | 0.021    |
| U5       | 0.0018                 | 1.81                  | 0                   | 23.104   | -0.82  | 0.0134   |
| U6       | 0.01                   | 10                    | 0                   | 26.313   | -0.1   | 0.021    |
| U7       | 0.0024                 | 2.439                 | 0                   | 23.736   | -0.76  | 0.0152   |
| Hour | Demand |
|------|--------|
| 1    | 148    |
| 2    | 173    |
| 3    | 220    |
| 4    | 244    |
| 5    | 259    |
| 6    | 248    |
| 7    | 227    |
| 8    | 202    |
| 9    | 176    |
| 10   | 134    |
| 11   | 100    |
| 12   | 130    |
| 13   | 157    |
| 14   | 168    |
| 15   | 195    |
| 16   | 225    |
| 17   | 244    |
| 18   | 241    |
| 19   | 230    |
| 20   | 210    |
| 21   | 176    |
| 22   | 157    |
| 23   | 138    |
| 24   | 103    |