Unit commitment problem solved with adaptive particle swarm optimization

Ramesh Babu Muthu, Venkatesh Kumar Chandrasekaran, Bharathraj Munusamy, Dashagireevan Sankaranarayanan
Department of Electrical and Electronics Engineering, St Joseph's College of Engineering, Chennai, India

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ABSTRACT

This article presents an innovative approach that solves the problem of generation scheduling by supplying all possible operating states for generating units for the given time schedule over the day. The scheduling variables are set up to code the load demand as an integer each day. The proposed adaptive particle swarm optimization (APSO) technique is used to solve the generation scheduling issue by a method of optimization considering production as well as transitory costs. The system and generator constraints are considered when solving the problem, which includes minimum and maximum uptime and downtime as well as the amount of energy produced by each producing unit (like capacity reserves). This paper describes the suggested algorithm that can be applied for unit commitment problems with wind and heat units. Test systems with 26 and 10 units are used to validate the suggested algorithm.

Corresponding Author:

Ramesh Babu Muthu
Department of Electrical and Electronics Engineering, St. Joseph's College of Engineering
Sholinganallur, OMR, Chennai, Tamilnadu, India
Email: rameshbabum@stjosephs.ac.in

1. INTRODUCTION

Generation scheduling is also called as unit commitment (UC) is a non-linear complex mixed-integer optimization problem that aims to distribute the total demand across all generating units while minimizing operating expenses, including both production cost and transition cost. The UC process involves meeting time specific constraints, balancing load demand, accounting for system losses, and ensuring reserve capacity. A crucial step in solving the UC problem in determining the hourly operational status of each generating unit, which then guides the allocation of power and reserve capacity throughout the planning horizon.

The maintenance of electrical network functionality is mostly the responsibility of UC [1]-[5]. Power system solution becomes more difficult as the number of producing units increases and the UC problems get exponentially more complex. Numerous strategies have been put forth to address the UC issue with the lowest operating cost feasible, increasing potential savings from the electricity network operator. However, there are differences in the accuracy and speed of their calculations. These methods can be separated into two categories: stochastic and deterministic search algorithms. Bound and branch methods (B&B), deterministic approaches include lagrangian relaxation differential evolution (LRDE), lagrangian relaxation (LR), and improved lagrangian relaxation (ILR) and dynamic programming (DP) [6]-[12].

For power systems of moderate size, these methods handle problems fast, accurately, and simply. For them, the challenges are in convergence, quality of solution, and intricacy. Some examples of heuristic or stochastic search methods are ant colony optimization, evolutionary programming, tabu search, and simulated annealing, fuzzy adaptive PSO (FAPSO), hybrid PSO (HPSO), discrete PSO (DPSO), genetic algorithms, and multi-objective PSO. Using the two categories of algorithms outlined above, a few hybrid algorithms are also proposed [13]-[25]. These methods produce highly optimal outcomes while handling difficult linear and nonlinear restrictions. All these approaches, however, suffer from the accuracy issue. The computational time and solution quality are both adversely affected by the larger problem and more generating units. This work proposes new approach by generating unit with all possible states of combination of each particle at each time step. By using the proposed APSO to optimize these particle states instead of any other technique mentioned above, the power system operator can achieve excellent results.

2. RESEARCH METHOD

2.1. Problem formulation

The primary goal of the generation scheduling problem is to ascertain the commitment status of the available thermal units to reduce the total operational expenses, which comprise startup, shutdown and production costs. This function can be optimized while taking into account all generator and system constraints.

2.1.1. Cost of production

Minimizing the overall production cost throughout the scheduling period while adhering to a set of generator limitations is the main goal of the UC problem. In (1) provides PCi for unit i, the quadratic production cos. Where, a_i, b_i and $c_i$are the coefficients of cost and p_i is the active power output in MW of the committed unit *i*.

$$pc_{\,i} = a_i + b_i p_i + c_i p_i^2 \tag{1}$$

2.1.2. Initial outlay

The initial contribution is the next part of the function that is the goal. Depending on the T_{Off} time (OFF), the starting cost can be determined by exponential starting cost and beginning (cold/hot) costs. The starting cost is referred to as a warm start if the cold start time is less than the total off-eak period (T_{Off}). If not, they are considered a cold start. The initial cost SCi for each period t is obtained from (2).

$$SUC_{i,t} = \sigma_i + \delta_i \left\{1 - \exp\left(\frac{T_{off}}{\tau_i}\right)\right\} \tag{2}$$

$$\sigma_i = \begin{cases} Cold\ start\ cost\ CSC_i \ \ when\ T_t^{off} \ \geq\ CT_i \\ Hot\ \ start\ cost\ HSC_i \ \ when\ T_t^{off} \ \leq\ CT_i \end{cases} (3) T_i^{off} =$$

$$\begin{cases} |INS_i| + D_1^{off} ifunitisOFFatinitialcondion \\ D_1^{off} ifunitgetsOFFfromitsONstate \end{cases} \tag{3}$$

The subsequent parameters are employed in this formulation, i denotes the cooling time constant; D_i^{off} denotes the off time before unit i comes into commitment; HSC_i stands for hot startup expenses; CSC_i for chill start-up expenses; and CTi stands for chill-start time. Limitation on the equilibrium of power. Capacity balance constraints ensure that the total power produced by each type of generating unit equals the power load for each time period.

$$\sum_{i=1}^{N} P_{i,t} U_{i,t} = P_{D,t} + P_{L,t} \qquad t = 1,2,3 \ldots\ldots T \tag{4}$$

The variables $P_{L,t}$ and $P_{D,t}$ represent the total losses and power demand at hour t in MW.

2.1.3. The rolling reserve limit

A rolling reserve is the underused capacity of grid energy assets that can momentarily offset frequency changes or power outages. Historically, huge synchronous generators were equipped with rotating reserves. P_{RR} represents the rolling reserve at time t and the i^{th} generator's upper bound limit is denoted by P_{max}.

$$\sum_{i=1}^{N} P_i^{max} U_{i,t} \geq P_{D,t} + P_{L,t} + P_{RR,t} \qquad t = 1,2,3, \ldots T \tag{5}$$

2.1.4. Zone of prohibited operation

Certain operating zones prevent the generators from producing real power because of mechanical stress or subsynchronous oscillations, which cause the unit to completely shut down. The reason behind the discontinuity in the fuel-cost curve is these regions, also referred to as prohibited operating zones. In zone of prohibited operation (POZ), generators are prohibited in real time. While poz_i and n_{poz} stand for units having forbidden zones and the number of restricted operating zones, respectively, P_i^u and P_i^l denote the maximum and minimum values of the ith generator within the prohibited operating areas.

$$P_{i,t} \in \left\{ \begin{matrix} p_i^{max} \le p_i \le p_{i,1}^{l} \\ p_{i,m-1}^{u} \le p_i \le p_{i,m}^{l} \end{matrix} \right. \qquad p_{i,poz_i}^{u} \le p_i \le p_i^{max} \tag{6}$$

m = 2,3,…,poz_i when, $U_{i,t}$=1
i = 1,2,…..,n_{poz}

2.1.5. Boundary constraint of the generator

The limitations of the upper and lower bounds specified here must be operated by the committed generators.

$$p_i^{max} \ge p_{i,t} \ge p_i^{min} \qquad when\ U_{i,t} = 1 \tag{7}$$

2.1.6. Minimum uptime/downtime limit

According to (8) the generators need a minimum amount of time to start during the cooling phase and stop during the running condition.

$$\left. \begin{matrix} (U_{i,t} - U_{i,t-1})(T_{on}(t-1) - MUT_i) \le 0 \\ (U_{i,t} - U_{i,t-1})(T_{on}(t-1) - MUT_i) \ge 0 \end{matrix} \right\} \tag{8}$$

Ton indicates the time the unit was turned on before the hour, and MUT_i and MDT_i is the lowest upper/lower time limit in hours for the i^{th} unit. Ton/Toff's value is represented as,

$$\left. \begin{matrix} T_{on}(t) = (1 + T_{on}(t-1)U_{i,t} \\ T_{off}(t) = (1 + T_{off}(t-1)(1 - U_{i,t}) \end{matrix} \right\} \tag{9}$$

2.1.7. Limitation on ramp rate

In mathematics, a generator's ramp up/down limit is expressed as,

$$\left. \begin{matrix} [p_{i,t-1} - DR_i(1 + U_{i,t})(U_{i,t-1})] \le p_{i,t} \\ [p_{i,t-1} - UR_i(1 + U_{i,t-1})(U_{i,t+1})] \le p_{i,t} \end{matrix} \right\} \tag{10}$$

2.2. Solution using APSO

The robustness and adaptability of stochastic optimization methods are making them increasingly attractive for solving non-linear optimization issues. A popular swarm-based, bio-inspired technique for solving optimization issues is called PSO. It is easy to use and highly efficient. Using velocities similar to birds, the population-based PSO algorithm modifies the starting population to determine the best route to take in order to arrive at the target. Similar to other population-based techniques, the conventional PSO can be limited to local minima.

The inertia weight and the random variables C1 and C2 are the primary determinants of the orientation of the solution search space in PSO. It is possible for the updated particles to become stuck in the local optimal solution when they fail to follow the leader. In this work, the quasi-oppositional learning technique proposed by Kumar and Babu [7] is integrated with the mutation operator. It was introduced to increase PSO's search capabilities and population variety. The formula provides the quasimutation operator,

$$\mathrm{X}_i^{q0} = \mathrm{rand}\ (\mathrm{X}_i^{C}, \mathrm{X}_i^{0}) \tag{11}$$

$$\mathrm{X}_i^{C} = \frac{\mathrm{X}_i^{max} + \mathrm{X}_i^{min}}{2} \tag{12}$$

$$X_i^0 = X_i^{max} + X_i^{min} - X_i \tag{13}$$

where $X_i^{min} and X_i^{max}$ are the minimum and maximum bound limits of ith individual's search space; X_i is the individual and X_i^0 is the opposite individual; X_{iq}^0 is a uniformly distributed random number between X_i^C and X_i^0.

The generation of quasi-opposite individuals is based on the leap rate (L_r). Although the technique does not entirely converge to the global optimum, it does converge rapidly to smaller values of L_r. Similarly, because of the wider search space, algorithms with larger L_r values may take a long time to converge. The jump rate selection should prevent early convergence and offer sufficient notable changes at baseline. As a result, the adaptive hop rate that this study employed to account for these issues is stated as:

$$L_r = L_{r,max} - \frac{L_{r,max} - L_{r,min}}{itermax} \times iter \quad (14)$$

where, $L_{r,min}$=0.01, $L_{r,max}$=0.5, iter is the current iteration, and itermax is the maximum iteration. To avoid premature convergence L_r is high at the starting and it is progressively reduced to improve the convergence rate.

The suggested algorithm uses the conventional PSO with the integration of quasi-oppositional learning-based mutation along with the adaptive leap rate, hence, it is called APSO. The pseudo code of the proposed APSO is given in Pseudocode 1.

Pseudocode 1. APSO pseudocode

```
Pseudo code: Adaptive Particle Swarm Algorithm
Initialize Xi, Vi, iteration, pbest, gbest
Generate random particles(P)
For each particle (i)
      Calculate fitness function (fi)
      Update pbest, gbest
End for
While iteration
      For each particle I
      Update Xi, Vi
      If Xi > limit, then Xi = limit
      Calculate fitness function fi
     Update pbest, gbest
     End for
End while
Check if any search agent goes beyond the search space and amend it
Calculate the leap rate Lr by equation 15
If rand (0, 1) < Lr
Compute quasi-opposite individual for integer variable by Equation 12
End
Calculate the fitness of each search agent
Update X* if there is a better solution
Update the value of F and Return
End
```

3. RESULTS AND DISCUSSION

MATLAB 9.4 (R2018a) contains the software for the suggested approach to addressing the UC problem. It runs on an Intel Core i5 with a CPU speed of 1.6 GHz and 8 GB of RAM running Windows 10. The suggested approach is tested on two test cases, and the outcomes are contrasted with a number of existing methods from the literature. Test case 1 is a rather conventional 10-unit system with a quadratic cost function and a rotating reserve. Test case 2 uses a 26-unit RTS system with a rotating reserve.

3.1. Test case 1

The data for the 10-unit system is presented in reference [7]. A spinning reserve of 10% of the system demand is established for that hour, while adhering to the MUT/MDT constraint. Since the valve-point and ramp rate constraints are not taken into account in this instance, the outcomes can be contrasted with those from previous research. Test case 1 employs a 10-unit system that consistently accommodates a variety of loads. The test system data is sourced from the literature references [7] and [12].

The stochastic nature of the meta-heuristic algorithms necessitates statistical analysis for validation. Table 1 presents the average, standard deviation, best, and worst results from 25 separate experiments. The table shows how close to the optimal cost the average cost achieved for several test cases is. The solution precision would be more advantageous for a complicated system with more units than for a system with fewer units. The Table 1 also shows the comparison of the results with other optimization algorithms. Ramp-rate limitations cause the computation time to grow. Comparable to other methods documented in the literature, the average computing time increases linearly with the number of units. The statistical analysis is presented in Table 1. The convergence characteristics of the proposed method is plotted in Figure 1.

Figure 2 shows the variation of spinning reserve and load demand. It's evident that spinning reserve will be accessible following the unit commitment procedure. A variation of total cost with respect to iteration is plotted in Figure 3, which shows the exploration and exploitation characteristics of the proposed algorithm. The load shared by each unit to meet the committed load of that hour is displayed in Figure 4. It makes it evident that the equality constraint is satisfied for all the hours. Figure 4 provides information regarding the total cost incurred for every iteration.

Table 1. An analysis comparing the 10-unit system's total cost

Total cost ($)	APSO	PSO	SSA
On Average (25 TRIAL CASE)	569687.2	564101	563945
WORST	575760	564110	563959
BEST	566136	564091	563937

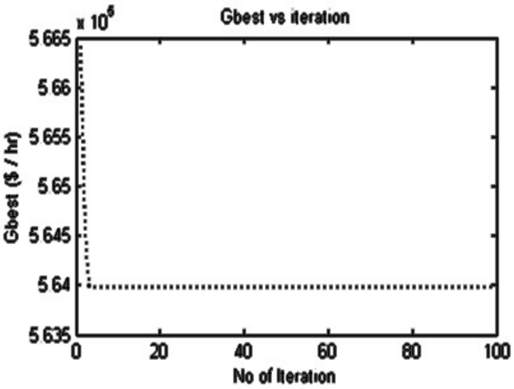

Figure 1. Convergence characteristics of 10-unit system

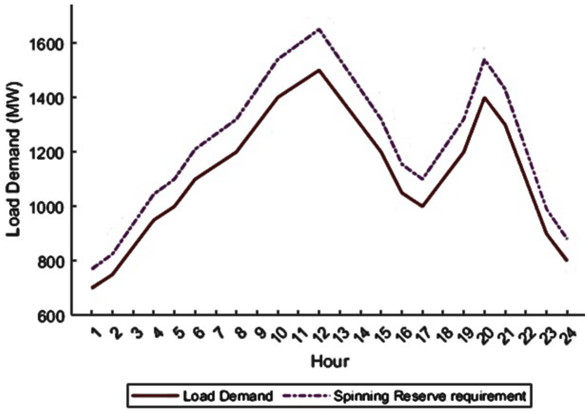

Figure 2. The 10-unit system's load requirement

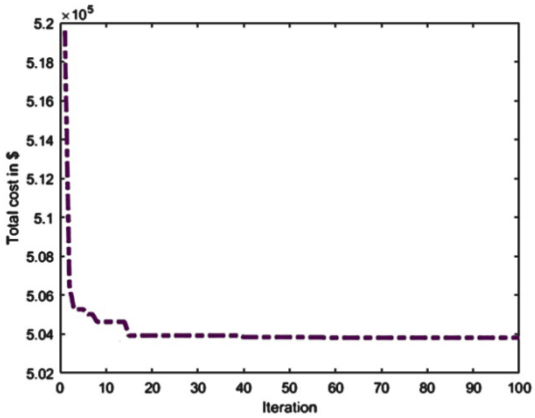

Figure 3. Total expense incurred in a ten-unit system

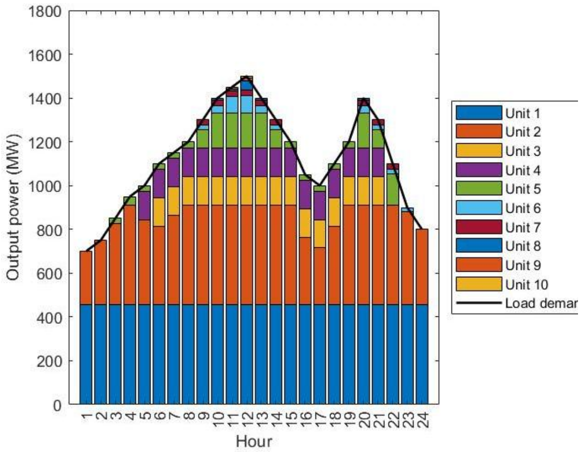

Figure 4. Power output in a system with ten units

3.2. Test case 2

A 26 unit system is considered as a second test case. Test system data for 26 unit system is taken from [7]. Using 26-units system, the generation scheduling problem is optimized using the APSO method. Table 2 tabulates the average, worst, and best results from the 25 trail runs. It is evident from the results that the suggested approach is also more dependable for larger systems. The 26-unit system's convergence characteristics are displayed in Figure 5. A graph comparing the load requirement and a load requirement with a constraint (a spinning reserve) is displayed in Figure 6.

Table 2. Statistical results obtained for the 26-unit system

Total cost ($)	APSO
Best	29,915
Average (25 trial case)	345,536
Worst	354,733

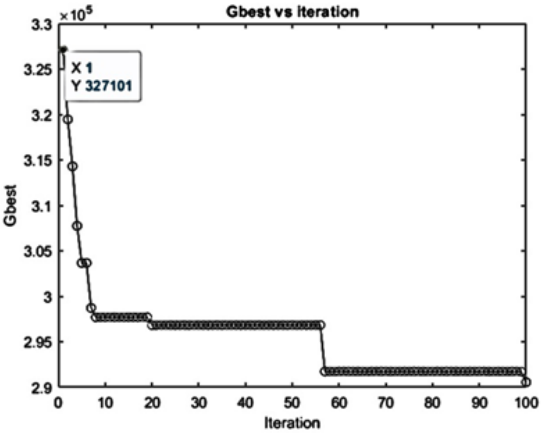

Figure 5. Convergence characteristics of 26 unit

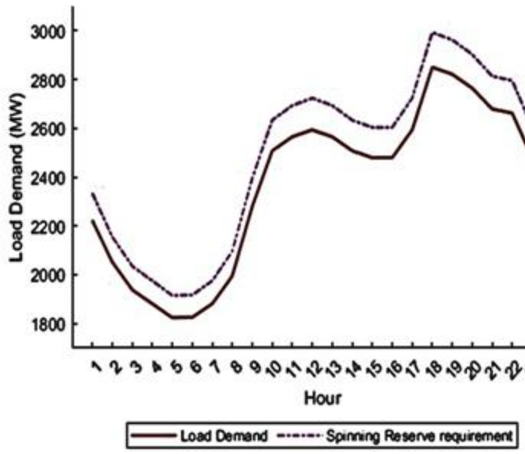

Figure 6. System's load demand

4. CONCLUSION

The challenging UC problem necessitates algorithms capable of effectively generating optimal outcomes concerning initial and operational costs. In comparison to other approaches, the advantageous characteristics of the proposed methodology yield enhanced tabulated results for UC. Recently, a population-based stochastic optimization technique known as logical state PSO has been introduced for the generation of discrete state particles. For certain intricate issues, such as UC in actual power systems, this PSO method delivers search results that are on par with or superior to those obtained from alternative stochastic optimization methods. Furthermore, the use of special convergence values can expedite the behavior of convergence, assisting particles in meeting the equality demand constraint and removing superfluous reserve allocation. The current study suggests that, in order to promote convergence and variety, the conventional public service requirement should be modified. Consequently, the algorithm can provide high-quality results and scan the search field quickly. A further adjustment to the suggested algorithm would take wind energy components into account, resulting in a stochastic unit commitment problem. Multiple restrictions are used in the suggested solution to the unit commitment problem in the existing system. By adding another variable source (renewable energy like solar or wind), we can produce a stochastic unit commitment problem. An uncontrolled power system's stochastic unit commitment problem can be created using the suggested algorithm. The power company controls distribution, maintains poles and wires, and bills customers for these services in a liberalized market.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ramesh Babu M	✓	✓		✓		✓	✓		✓		✓	✓	✓	✓
Venkatesh Kumar C			✓	✓	✓			✓		✓	✓			
Bharatraj M,			✓		✓	✓		✓		✓	✓			
Dhasagreevan S			✓		✓	✓		✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Ramesh Babu Muthu received a B.E degree in electrical and electronics engineering from Madras University, Chennai, India, in 1998, and an M.E. degree in power systems engineering from Thiagarajar College of Engineering, Madurai, India, in 2000. He received Ph.D. in power system engineering from Anna University in 2013. He is currently a Professor in the Department of Electrical and Electronics Engineering, St. Joseph’s College of Engineering, Chennai. His research interests include applications of computational intelligence techniques to power systems, distributed energy resources and smart grid. He can be contacted at email: rameshbabum@stjosephs.ac.in.

Venkateshkumar Chandrasekaran received his bachelor’s degree in electrical and electronics engineering and Masters in Power systems Engineering from Anna University, Chennai in the years 2006 and 2010. He received Ph.D. in power system engineering from Anna University in 2023. He is currently a Assistant Professor in the Department of Electrical and Electronics Engineering, St. Joseph’s College of Engineering, Chennai. His fields of interest include power system deregulation, smart grid, and power system planning. He can be contacted at email: venkateshkumarc@stjosephs.ac.in.

Bharathraj Munusamy from Thiruvannamalai, Chengam, an undergraduate student at St. Joseph’s College of Engineering specializes in the niche field of power systems and optimization. He has actively engaged in a range of technical tasks and has a strong interest in machine learning. His contributions are intended to offer important new understandings and developments in these quickly developing domains of study. He can be contacted at email: bharathrajm19@gmail.com.

Dhasagreevan Sankaranarayanan an undergraduate student at St. Joseph's College of Engineering, is specializing in the niche field of embedded programming and theoretical embedded logic within the Department of Electrical and Electronic Engineering. He has a profound interest in theoretical physics and machine learning and has actively participated in a variety of projects. These experiences have allowed him to explore the fascinating intersection of machine learning, theoretical physics, and electrical engineering. He can be contacted at email: dashagireevan07@gmail.com.