Contemporary Mathematics
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Research Article

Synergistic Optimization of Unit Commitment Using PSO and Random Search

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Received: 8 September 2023; **Revised:** 21 September 2023; **Accepted**: 27 September 2023

Abstract: Optimizing the order of thermal units for power generation plays a pivotal role in meeting load demand while minimizing fuel consumption. This paper introduces an enhanced hybrid method designed to schedule generating units with the simultaneous objectives of cost and emission reduction, which often pose a trade-off challenge. The hybrid approach integrates the parametric adaptation of particle swarm optimization (PSO) with the randomness of a random search algorithm. The introduction of intermediate variables enhances the performance of particles in the PSO framework, contributing to more effective optimization. To update the individual population's locations within the particle swarm optimization process, randomness is judiciously introduced using a random search method. To assess the potential of the proposed method, it is applied to the IEEE-39 bus system and a four-unit thermal system. The results obtained through the proposed approach are compared with those achieved by existing methods, demonstrating its effectiveness in achieving optimal solutions for the unit commitment problem.

Keywords: optimization, thermal units, particle swarm optimization, random search algorithm, hybrid method

MSC: 90C27, 90C31, 32C05, 32C07.

1. Introduction

The demand for the electricity is increasing rapidly across the World [1-3]. Applied mathematics plays a key role for designing the many concepts of electric sector [4-6]. In the field of electrical power systems engineering, power generation from thermal units is a significant focus among all power production systems. In the electric power market, utilities emphasize thermal power generation to efficiently balance load demand. Continuous power generation for variable load demands necessitates the sequential operation of thermal units. Predicting thermal unit on/off status helps prevent unnecessary fuel consumption. This concept is known as unit commitment in power systems. Unit commitment involves scheduling thermal units with on/off status [7], leading to reduced fuel consumption and cost. Proper unit commitment planning benefits the economy by maintaining

DOI: https://doi.org/10.37256/cm.5120243638

system constraints [8]. The unit commitment (UC) optimization problem is non-convex, nonlinear, discrete, and multi-constrained, encapsulating economic dispatch and commitment decisions. As constraints increase, problem complexity rises. Researchers have focused on minimizing fuel consumption costs [9]. In the power sector, managing power generation schedules to meet load demand is challenging due to new objectives and constraints. Emissions from thermal power plants pose environmental risks. To address this, the United States introduced an emissions reduction amendment in 1990 [10]. Many treat emissions as constraints in mono-objective optimization problems, hindering optimal solutions [11]. This led researchers to consider emissions as objectives, turning single-objective problems into multi-objective ones. Optimizing thermal unit scheduling aims to minimize production costs and emissions, a challenging task in UC optimization problems [12]. Various techniques have been applied to solve UC optimization problems. Numerous techniques have been proposed to achieve optimal solutions for UC optimization. New techniques regularly address previous methods' drawbacks. Some conventional methods include the Lagrangian method (LM) [13], Priority list method (PL) [14], dynamic programming method (DP) [15], and mixed integer method (MI) [16]. These methods are simple and fast but may suffer from solution quality and numerical convergence issues. Heuristic techniques include the tabu search method (TS) [17], Particle swarm optimization (PSO) [18-19], Simulated Annealing (SA) [20], Genetic Algorithm (GA) [21], Differential evolution (DE) [22], Niched pareto genetic algorithm (NPGA) [23], semidefinite programming (SP) [24], and self-adaptive learning bat algorithm (SDLBA) [25]. Each evolutionary algorithm technique has its merits and demerits. This method addresses classical method deficiencies and handles high constraints effectively. Heuristic techniques are suitable for moderate and normal networks in power systems. Another class of techniques is meta-heuristic, emphasizing generating superior solutions within a defined timeframe. These techniques are based on heuristic methods but are problem-agnostic, often mimicking biological and physical processes. A third class of techniques is hybrid methods, combining two or more heuristic methods for improved performance [26-36]. Hybrid meta-heuristics often outperform individual methods. Examples include Augmented Lagrange Hopfield network with a priority list (ALH & PI) [26], Dynamic programming with Hopfield neural network (DP & HNN) [27], Imperialist competitive with particle swarm optimization (IC&PSO) [28], Lambda iteration with simulated annealing technique (LI & SA) [29], non-dominant sorting genetic algorithm-II with Population Variant Differential Evolution (NSGA-II & PVDE), and Tabu search with simulated annealing (TS & SA) [30], among others. Hybrid methods combine the strengths of two techniques to focus on solving complex problems effectively [37]-[47]. Randomness exists in many optimization techniques, leading to increased iteration times [31]-[36]. This paper contributes by reducing randomness when updating particle positions in PSO using a random search method, applied to mono and multi-objective UC problems. Acceleration coefficients are assigned with intermediate variables in PSO to improve particle performance. In this paper, we propose a hybrid method that combines a random search algorithm with PSO to achieve an optimal solution to the UC optimization problem.

The rest of the paper is organized as follows: Section 2 defines the objectives' functions. Section 3 outlines the methodology for predicting optimal solutions to optimization problems. Section 4 discusses the simulation results and provides their analysis, while Section 5 offers the conclusion.

2. Materials and methods

2.1 *Formulation of Objective Function*

This section covers the objective function of the proposed method, and its constraints are discussed. The fuel cost is a quadratic function, and which can be expressed as (1).

$$\mathrm{F_y}\left(Pg_y(z)\right) = a_y + b_y Pg_y(z) + c_y Pg_y^2(z) \tag{1}$$

In (1), $Pg_x(y)$ is true power produced by the corresponding unit x at time y and $a_{x,} b_x, c_x$ are the cost coefficients and the corresponding startup and shutdown cost is identified as

$$SUC(y) = \begin{cases} HC(y), & if MD(y,z) \leq TC(y) \leq MD_{zo} \\ CSC(y), & if TC(y) > MD_{zo} \end{cases} \tag{2}$$

$$MD_{zo} = MD(y,z) + CST(y) \tag{3}$$

In this study, the HC and CSC are the hot start-up and cold start-up cost of y^{th} unit, MD_y is the minimum downtime of unit y, $TC(y)$is the off duration of unit y. The objective function is represented by (4).

$$min \sum_{y=1}^{M} \sum_{z=1}^{T} \left[F_y\left(Pg_y(z)\right) + SUC_y\left(1 - U_y(z-1)\right)\right] U_y \tag{4}$$

In (4), the M is number of generating units, T for 24 hours, U_y is the generating unit's on/off status and the unit commitment constraints.

A) Power balance constraint:

Generation level must equalize to demand $d_o$the level at an hour z.

$$\sum_{y=1}^{M} P_y(z).I_y(z) = d_o(z) \tag{5}$$

B) Spinning reserve:

A reserve capacity to maintain in the system is expressed as (6).

$$\sum_{y=1}^{M} P_y(z).I_y(z) \geq d_o(z) + SR(z) \tag{6}$$

C) Generation Range:

The generation of thermal power limits of each one is expressed as (7)

$$P_{y,min} \leq P \leq P_{y,max} \tag{7}$$

In equation (7), the $P_{y,max} and P_{y,min}$ are the higher and lower power limits of the y^{th} unit.

D) Minimum up and downtime:

The ON/OFF time of each unit is given by (8)

$$X_{y,on} \geq MUT_y \tag{8}$$

$$X_{y,off} \geq MDT_y \tag{9}$$

In equations (8) and (9) the $X_{y,on}$ and $X_{y,off}$ is the on/off duration of time y.

2.2 *Methodology*

This section deals with methodology of the proposed hybrid optimizations, which includes the parametric adaption of PSO, implementations of algorithms of PSO and RSO.

2.2.1 *Parametric adaptation of PSO*

In PSO, the particles are identified as potential solutions with two vectors, positions, and velocity. For 'd' dimensions of search space the positions and velocities for q[th] particle are prescribed as P = (P_{q1}, $P_{q,2}$, P_{q3}, ...P_{qd}); Vq= (V_{q1},V_{q2},V_{q3}....V_{qd}). Over the respective ranges, the positions and velocities are assigned with random vectors. The updating of new positions and velocities is represented by equation (9).

$$V_{qd}^{l+1} = Z * v_{qd}^{l} + c1 * rand * \left(PB_{qd} - p_{qd}^{l}\right) + c_2 * rand * \left(GB_{qd} - p_{qd}^{l}\right) \tag{10}$$

$$p_{qd}^{l+1} = p_{qd}^{l} + v_{qd}^{l+1} \tag{11}$$

In (10), the $c1$ and $c2$ are the acceleration coefficients, PB_{qd} is the best fitness position of q[th] particle in d dimensions, and the $rand$ is the random number. The the $c1$ and $c2$ can be evaluated by using the parameter φ where enhancement performance of particle P_q is given by equation (12).

$$H\left(P_q\right) = \frac{F(P_q(m_o)) - F(P_q(m))}{F(P_q(m_o)} \tag{12}$$

In (11), the m_o the initial moment, m is the present moment of the particle and the intermediate variable ω predicts the enhanced performance of the particle which is a greater or less current threshold if '$\omega \geq 0$' indicates improved in the performance of the particle and 'ω'< 0 indicates no improvement in performance.

$$\omega_q \geq 0 \quad \{\delta\varphi = \left(\varphi_{max} - \varphi_q\right)\omega_q \text{ (H=}\omega_q\text{)} \tag{13}$$

$$\omega_q < 0 \ \{\delta\phi = \left(\varphi_q - \varphi_{min}\right)(k) \tag{14}$$

$$\varphi_q = \varphi_q + \delta\varphi \tag{15}$$

$$o_1 = \frac{1}{\varphi_q - 1 + \sqrt{\varphi_q{}^2 - 2\varphi_q}} \tag{16}$$

$$C_{max} = \varphi * o_1; \tag{17}$$

$$C_1 = C_2 = C_{max}; \tag{18}$$

$$Z = (Zmax - Zmin) * \frac{iter_{max} - iter}{iter_{max}} + Z_{min} \tag{19}$$

In (19), the $iter_{max}$ and $iter$ are the maximum and present iteration, Z is the inertia weight parameter, and k is the negative of the current performance of the particle q.

A step-by-step procedure for implementation of proposed PSO algorithm is given by.

Step- 1: Initialize the parameters, such as swarm particle positions randomly, velocity, and maximum iteration.

Step- 2: Predict the strength for all particles, $Pbest$, and select $gbest$. Evaluate the parameters $c1$ and $c2$ using equations (12) to (16). Update velocities and positions using equations (9) and (10).

Step- 3: Evaluate the economic load dispatch for each particle solution and calculate the fitness value.

Step- 4: Update the $Pbest$ and $gbest$ positions. If the iteration reaches the maximum value, stop the iteration; otherwise, go to Step 2.

2.2.2 *Random Search Algorithm*

The Random Search Algorithm is one of the meta-heuristic methods. In this method, probability and randomness are implemented. RSA is suitable for evaluating global optimization in non-differential, non-convex, and discrete objective functions. RSA [36] effectively handles tedious, complex, and large-scale problems. It is categorized as a two-phase method, including instant-based and model-based approaches. The steps for RSA are as follows:

Step-1: Initialize initial parameters, such as the number of iterations and the size of the population.

Step-2: Generate random solutions for each iteration based on the problem size.

Step-3: Evaluate the fitness value of the random solutions and determine the best minimal solution.

Step-4: During each iteration, compare the fitness of the randomly generated solutions with the best solution.

Step-4: After reaching the maximum iteration (i.e., the stopping criteria), finally return the best candidate solution, considered the global optimal solution. The flowchart of the hybrid method is shown in Figure 1.

3. Results and Discussions

The proposed hybrid method has been tested on two test systems. The first test system is a four-unit system with the single objective of cost minimization over an 8-hour dispatch period. The second test system is an IEEE 39-bus system with 10 thermal units, involving multiple objectives - both cost and emission minimization, over a 24-hour dispatching period.

In Case (i) of this study, a four-unit system is addressed using a combination of heuristic and meta-heuristic methods, specifically the parametric adaptation of particle swarm optimization and the random search method. Initial parameters, including a population size of 40, a maximum iteration limit of 20, and a dimension count of 8, are initialized. Data related to cost coefficients, maximum and minimum power limits of thermal units, startup costs, minimum downtime, minimum uptime, and corresponding load demands for eight hours, are obtained [30]. The commitment and decommitment of power-generating units over this 8-hour period are shown in Table 1. For low loads, only two thermal units are committed, while for high loads, three thermal units are committed, as illustrated in Table 1.

Table 1: Status of thermal units.

Hour	Pg_1	Pg_2	Pg_3	Pg_4
1	1	1	0	0
2	1	1	0	0
3	1	1	1	0
4	1	1	1	0
5	1	0	1	1
6	1	0	1	0
7	1	0	0	0
8	1	1	0	0

Table 2: Scheduling of thermal units and their total cost.

Pg_1 (MW)	Pg_2 (MW)	Pg_3 (MW)	Pg_4 (MW)	SUC ($)	Cost ($)	Total cost ($)
300	150	0	0	0	9145.36	9145.36
300	230	0	0	0	10629.04	10629.04
300	250	50	0	150	12262.86	12412.86
300	215	25	0	0	11079.38	11079.38
300	0	80	20	0.02	8531.82	8531.84
255	0	25	0	0	5845.568	5845.568
290	0	0	0	0	5742.05	5742.05
300	200	0	0	170	10066.36	10236.36
				320.02	73302.44	73622.46

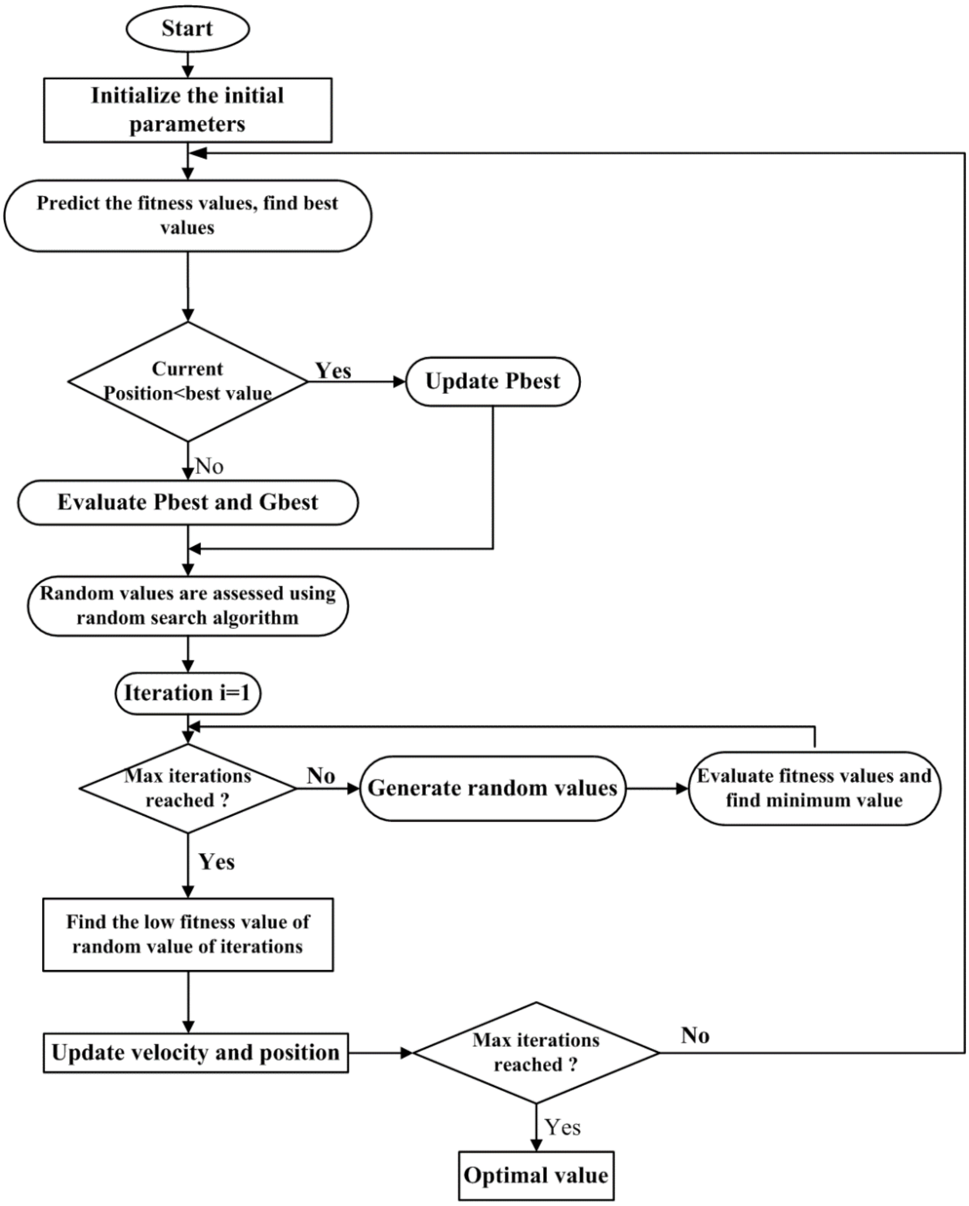

Figure 1: Flowchart of proposed hybrid algorithm.

Table 2 illustrates the dispatching of various load demands with committed thermal units, their startup costs, and the total cost. In this case, a high-rated thermal unit is committed to all different load demands over the eight-hour period, while a low-rated thermal unit is committed to only one load demand, which is 400 MW. The startup cost is $ 320.2, and the total cost amounts to $73,622.46. The obtained optimal value is compared with existing methods, as shown in Table 3.

Table 3: Comparison of the proposed method total cost with other existing methods.

Method	Cost ($)
Improved Lagrangian relaxation [38]	75,231
Lagrangian relaxation and PSO [38]	74,808
Binary differential evolution [34]	74,676
Genetic algorithm (GA) [35]	74,675
Proposed Method	73,622.4

When comparing the optimal solution obtained through the proposed method with Genetic Algorithm (GA), a cost reduction of $1052.6 is observed, indicating a superior optimal solution. In comparison with ILR, there is a reduction of 1.4%.

Case (ii):

In this case study, the IEEE 39 bus system is addressed using the proposed method. It involves two conflicting objectives - cost and emissions - which are considered for minimization and transformed into a single objective function with min/max criteria. The optimization problem is subject to both inequality and equality constraints. The relevant data for the IEEE-39 bus system with 10 thermal units is taken from [44]. Initial parameters are assigned their respective values, and both equality and inequality constraints are considered. Spinning reserve is set at five percent. The commitment and decommitment of the ten thermal units over a 24-hour period are detailed in Table 4. The last thermal unit is committed to high load demand, while the first thermal unit is committed to all different loads. The dispatching of various load demands with the on/off status of thermal units is illustrated in Table 5.

Table 4: Thermal units of IEEE-39 bus system.

S. No	Pg1	Pg2	Pg3	Pg4	Pg5	Pg6	Pg7	Pg8	Pg9	Pg10
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	0	0	0	0	0	0
4	1	1	0	0	1	0	0	0	0	0
5	1	1	0	0	1	0	0	0	0	0
6	1	1	1	0	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	0	1	0	0	0
10	1	1	1	1	1	1	1	0	1	0
11	1	1	1	1	1	1	1	1	0	0

12	1	1	1	1	1	1	1	1	1	0
13	1	1	1	1	1	1	1	1	0	0
14	1	1	1	1	1	0	1	0	0	0
15	1	1	1	1	1	0	1	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	1	0	1	0	0
19	1	1	1	1	1	1	0	1	0	0
20	1	1	1	1	1	1	1	1	0	0
21	1	1	1	1	1	0	1	0	0	0
22	1	1	1	0	1	0	1	0	0	0
23	1	1	0	0	0	0	0	0	1	0
24	1	1	0	0	0	0	0	0	0	0

Table 5: Scheduling of load demand of IEEE 39-bus system for 24 hours.

$Pg_{1(MW)}$	$Pg_{2(MW)}$	$Pg_{3(MW)}$	$Pg_{4(MW)}$	$Pg_{5(MW)}$	$Pg_{6(MW)}$	$Pg_{7(MW)}$	$Pg_{8(MW)}$	$Pg_{9(MW)}$	$Pg_{10(MW)}$
455	245	0	0	0	0	0	0	0	0
455	295	0	0	0	0	0	0	0	0
455	395	0	0	0	0	0	0	0	0
455	455	0	0	40	0	0	0	0	0
455	455	0	0	90	0	0	0	0	0
455	455	130	0	60	0	0	0	0	0
455	410	130	130	25	0	0	0	0	0
455	455	130	130	30	0	0	0	0	0
455	455	130	130	105	0	25	0	0	0
455	455	130	130	162	33	25	0	10	0
455	455	130	130	162	80	25	13	0	0
455	455	130	130	162	80	25	53	10	0
455	455	130	130	162	33	25	10	0	0
455	455	130	130	105	0	25	0	0	0
455	435	130	130	25	0	25	0	0	0
455	310	130	130	25	0	0	0	0	0
455	260	130	130	25	0	0	0	0	0
455	330	130	130	25	20	0	10	0	0
455	430	130	130	25	20	0	10	0	0
455	455	130	130	162	33	25	10	0	0
455	455	130	130	105	0	25	0	0	0
455	455	130	0	35	0	25	0	0	0
455	435	0	0	0	0	0	0	10	0
455	345	0	0	0	0	0	0	0	0

From Table 5, it can be illustrated that the generation of power from thermal units is expressed in terms of Megawatt. The generated power from the thermal units must satisfy the corresponding constraints.

Table 6: Total cost and emission values of IEEE-39 bus system.

S. No	Load (MW)	SUC ($)	COST ($)	Total Cost ($)	Emission (lb)
1	700	0	13683.12	13683.13	943.84
2	750	0	14554.49	14554.5	1015.86
3	850	0	16301.88	16301.89	1206.70
4	950	900	18597.66	19497.67	1341.40
5	1000	0	19608.53	19608.54	1344.69
6	1100	1100	21891.42	22991.43	1373.77
7	1150	1120	23261.97	24381.98	1299.56
8	1200	0	24150.34	24150.34	1409.04
9	1300	520	26842.13	27362.13	1408.42
10	1400	400	30075.85	30475.86	1426.72
11	1450	60	31219.62	31279.63	1426.26
12	1500	30	33205.25	33235.25	1419.44
13	1400	0	30057.55	30057.55	1426.77
14	1300	0	26842.13	26842.13	1408.42
15	1200	0	24874.02	24874.02	1352.50
16	1050	0	21513.65	21513.66	1099.36
17	1000	0	20641.82	20641.82	1022.66
18	1100	230	23600.48	23830.49	1124.72
19	1200	0	25350.04	25350.05	1337.39
20	1400	260	30057.55	30317.55	1426.77
21	1300	0	26842.13	26842.13	1408.42
22	1100	0	22563.46	22563.47	1368.29
23	900	60	17940.50	18000.5	1297.01
24	800	0	15427.41	15427.42	1103.48
		4680	559103.148	563783.1	30991.61

The startup cost, fuel cost, total cost, and emission values for the IEEE 39 bus system are presented in Table 6. To calculate the total cost for different load demands, the fuel cost values and startup cost values are summed. The resulting total cost value is $563,783.1, and the emission value is 30,991.61 lb, as shown in Table 6. Corresponding graphs depicting these values over time are displayed in Figures 2 and 3. The obtained optimal value using the hybrid method is compared with literature methods, as illustrated in Table 7.

Table 7: Comparison of cost and emission values of IEEE-39 bus system

Method	Cost ($)
Improved binary particle swarm optimization [45]	599,782

Particle Swarm optimization [46]	581,450
Hybrid PSO-SQP [47]	568,032
Proposed Method	563,783

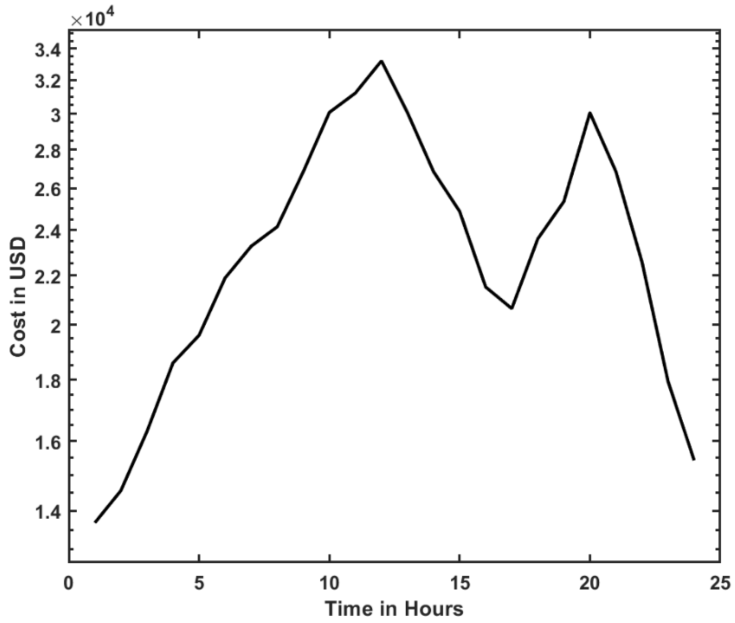

Figure 2: Total Cost in USD versus Time in hours.

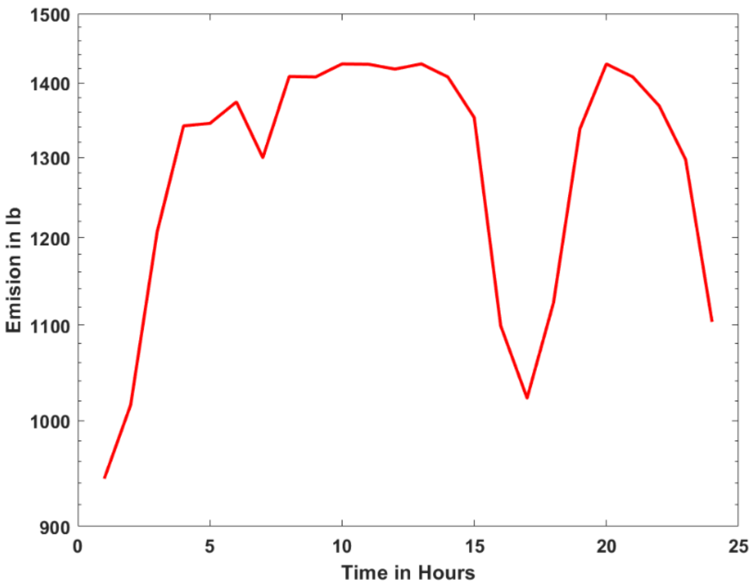

Figure 3: Emission in lb versus Time in Hours.

4. Conclusions

This study harnesses the power of a hybrid approach that combines heuristic and meta-heuristic algorithms to predict optimal solutions for the unit commitment optimization problem. The integration of these techniques facilitates a comprehensive assessment of the scheduling process, ultimately leading to enhanced efficiency. Incorporating parametric adaptation into PSO improves the performance of individual particles.

Simultaneously, the introduction of a random search method evaluates the role of randomness in refining these optimizations. To gauge the potential of our proposed hybrid method, rigorous testing was conducted on two distinct test systems. The first system comprised a four-unit setup focused on single-objective cost minimization, while the latter featured a more complex 10-unit system. Our simulation results consistently revealed superior optimal values compared to existing methods.

Conflict of interest

There is no conflict of interest for this study.

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