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A Hybrid Social Sky Driver Optimizer Approach for Solving the Generation Scheduling Problem

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ABSTRACT

In order to address the generation scheduling issue, this research suggests a novel hybrid optimization method. Two popular metaheuristic search algorithms, Social Sky Driver (SSD) and Sine Cosine Optimizer (SCA), are hybridized to create a hybrid optimizer. The power system thermal unit commitment problem can be resolved with the suggested optimizer SSD-SCA. Without considering time limitations, minimum-up and minimum-down time requirements are disregarded. Finding a feasible commitment and then trying to make the solution more optimal are the main goals of the approach covered in this article. constraints that are fixed separately using heuristic techniques. Lastly, the optimal power generation is obtained by applying the quadratic programming method. The broad 10-unit system confirms the usefulness and effectiveness of the proposed method. The results unequivocally show that proposed method provide better results as compared with other conventional method.

Keywords: Generation scheduling, metaheuristic algorithm, Economic load dispatch

INTRODUCTION

The main goal of the generation scheduling issue in a harmonized power system is to obtain the lowest cost of power generation by spreading the best generation across all participating units while fulfilling different limitations and eventualities [1]. Conventional technique to solve generation scheduling is not economical in true sense, because in this approach all the generating units considered running all the time but since load demand is never the same in two consecutive intervals. It can touch peak at particular interval and valley in different interval. Hence if load is low for appreciably time some units may be shut down for that interval.

The optimal generation scheduling problem is a composite problem resulting from the combination of two sub problems. [1]The first is the unit commitment problem (UCP), which decides whether a unit will participate or not. The second is the startup and shut down schedule for all available units. The search of such combinations are necessary to minimize system fuel expenditure. Other problem is economic dispatch problem (ELD) which assigns load demand in the committed units for minimizing power generation.

2 LITERATURE SURVEY

Baldwin wrote one of the first studies in the subject of unit commitment in 1959 [2]. From the conventional epoch to the contemporary soft computing epoch, a significant amount of study has been done in the subject of unit commitment problems. Thermal UC deterministic methods include, Exhausted Enumeration Priority List,[2][3] Dynamic Programming[4][5][6][7] Lagrangian Relaxation[8] sequential Method decommitment method Integer Programming (IP)[9] Branch-and-Bound (BB),[10] Branch and cut[11] Mixed Integer Programming (MIP) [12] Mixed integer quadratic programming [13], Tabu search[14].Many of the aforementioned solutions are confronted with the question of dimensionality, particularly for large systems. The soft computing methods are used to counter mathematical solution demerits. Soft computational techniques such as: Evolutionary programming [14][15]Genetic Algorithm (GA)[16][17][18], Simulated Annealing (SA)[19]Neural Network (NN) [20]Differential Evolution (DE)[21], Harmony Search(HS)[22] Ant Colony System (ACS) [23]algorithm Bacterial Foraging Algorithm (BFA)[24] Shuffled Frog Leaping Algorithm (SFLA)[25] Particle Swarm Optimization (PSO)[26][27], Biography Based Algorithm(BBO)[28], Seeker optimization algorithm [29] Teaching Learning Based Optimization algorithm(TLBO)[30][31] Learning Based

Optimization based on Quasi- Oppositional Teaching (QOTLBO) [32] and Offensive or invasive Weed Optimization (IWO) [33] and Fireworks Algorithm [34] have been reported in the field of thermal UC.Hybrid methods include Hybrid Taguchi (HT) - ACS LR and PSO hybrid harmony search/random search algorithm [35] and PSO-SCA[36] PL-PSO Algorithm [37] have been reported to solve thermal generation and scheduling problems.

Meta-heuristic optimization approaches have grown increasingly popular in recent years. These optimization approaches have been used in a variety of disciplines of research.[38] Meta-heuristics are straightforward. They are inspired by very simple notions such as physical occurrences, animal behaviours, and evolutionary theories.[39] Meta-heuristics are simple to apply to a variety of issues. Finally, meta-heuristics outperform standard optimization techniques in terms of avoiding local optima. Meta-heuristics are feasible options for optimizing these tough real-world problems since the search space of genuine issues is typically unknown and complex, with a high number of local optima.[40]

There is no one-size-fits-all meta-heuristic that can solve all optimization issues. This is finding of “No free lunch theorem”[41] To put it another way, a meta-heuristic may produce highly promising findings for a collection of issues. Even yet, the same algorithm may perform poorly on a different set of tasks. Furthermore, Meta-heuristics' simplicity allows us to suggest new meta-heuristics, combine two or more meta-heuristics, or enhance existing meta-heuristics. Hence it is envisaged to prepare a new hybrid Meta-heuristic search algorithm, For hybridizing purpose two well-known metaheuristic algorithm SMA[42] and SOA[43], which are recently developed is hybridize to solve generation scheduling problem should have both exploration and exploitation search techniques to solve unit commitment and dispatch problem of realistic power system integrated .

3. BRIEF NARRATIVE OF SSD

A unique optimization method Developed by, A. Tharwat and T. Gabel, [44] based on the behavior of existing evolutionary optimization algorithms. The Social Sky Driver (SSD) algorithm is the name of this algorithm. SSD's stochastic exploration mirrors the path that sky-drivers follow downwards, as its name suggests. The many SSD parameters are shown below.

- The position of the agents **(** $X_i \in \Re^n$ **)** is utilised to calculate the goal function at that point. The dimension of the search space is represented by n.
- *Previous best position* (**Y_i**): Each agent's fitness values are determined using the fitness function, and these values are compared to its present position. As a result, the most advantageous position is saved. This strategy is comparable to PSO in several ways.
- *Mean global solution* (**M_i**): The SSD algorithm works in the same way as the Gray Wolf Optimizer (SCA), with the agents moving towards the global point. The average of the top three answers is shown as:

$$M=\frac{X_\alpha+X_\beta+X_\gamma}{3} \tag{1}$$

where X_α, X_β, and X_γ are the best three solutions.

- *Velocity of the agents* (**V_i**): The agents’ positions are updated by adding the velocity V_i as follows:

$$X_i^{t+1}=X_i^t+V_i^t, \tag{2}$$

$$V_i^{t+1}=\begin{cases} c\sin(r_1)\,(Y_i^t-X_i^t)+\sin(r_1)(M_i^t-X_i^t) & if\ r\le 0.5 \\ c\cos(r_1)(Y_i^t-X_i^t)+\cos(r_1)\,(M_i^t-X_i^t) & if\ r>0.5 \end{cases} \tag{3}$$

Where V_i represents velocity of X_i and r_1, r_2 are evenly produced random values in the range [0,1]. V_i Is the i^{th} agent's best solution, M_i is the mean global solution for the whole population, and c is a parameter that is used to calculate the balance between exploration and exploitation.

$$C^{t+1}=\alpha * C^t \tag{4}$$

where t is the current iteration and $0<\alpha<1$ is used to reduce the value of c. Hence, $c\rightarrow 0$, where $t\rightarrow t_{max}$ and t_{max} is the maximum number of iterations. Because of the sine and cosine functions the moving direction for the agents are not straight forward, as in the case of SCA and PSO. A simple example of how two agents move in SSD algorithm is visualized in fig(1) This provides better guided exploration ability to proposed algorithm which makes the search directions to be diversified, but in the guided mode.

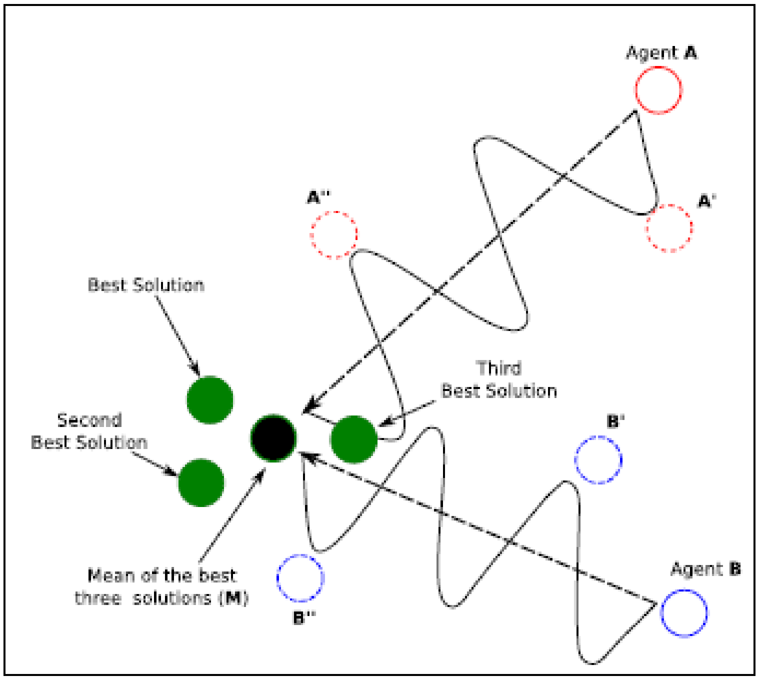

Fig (1): Social Sky Driver Optimizer: Strategy

SSD seeks to look for optimal and near-optimal solutions in the area. The size of the space are determined by the number of parameters that must be optimized. The locations (Xi) of agents are randomly initialized in SSD, and the user determines the number of agents. The locations of the agents are updated by adding a velocity to the old positions, as given in Eq (2). The velocities of the agents are randomly started and changed in accordance with Eq (3). The adjusted velocity of the agents is determined by (a) the distance between the current location Xit and the prior best position Yi, and the distance between the current position Xit and the mean global solution Mi, according to Eq(1). As a result, in SSD, the agents tend to gravitate toward the middle of the best three answers. As a result, the SSD algorithm is more sociable than the PSO algorithm. SSD's agents also do not move in a straight line, allowing for better exploration. The SSD algorithm is as follows:

ALGORITHM 1 SSD Algorithm

1. Initialize the agents' positions X_i and velocities V_i. Assume the system function is minimum.
2. **while** stopping criteria are not met **do**
3. **for all** agents **do**
4. Calculate the fitness values.
5. Sort the agents according to their fitness values.
6. Calculate previous best position and mean global solution.
7. Generate a new solution by updating the agents' positions as denoted in Eq (2).
8. Adjust the velocities of the agents as in Eq (3).
9. **end for**
10. **end while**
11. Return the best solution.

4. BRIEF NARRATIVE OF SCA

Any optimizer is unique in sense how position it update the random generate positions. SCA algorithm updates its position in following manor:

$$z_{t+1}^{i} = z_{t}^{i} + r_1 \times \sin(r_2) \times \left| r_3\, P_t^{i} - z_t^{i} \right|$$
$$z_{t+1}^{i} = z_{t}^{i} + r_1 \times \cos(r_2) \times \left| r_3 P_t^{i} - z_t^{i} \right| \tag{7}$$

In equation (8) z_t^i indicate current solution. It is basically position. $i\, and\, t$ Characterizes dimensions and iteration count. P_t^i Is position of terminus point? It is basically a destined points. Exploration and exploitation process balances by following equations:

$$z_{t+1}^{i} = \begin{cases} z_t^i + r_1 \times \sin(r_2) \times \left| r_3\, P_t^i - z_i^t \right| & r_4 < 0.5 \\ z_t^i + r_1 \times \cos(r_2) \times \left| r_3 P_t^i - z_t^i \right| & r_4 \geq 0.5 \end{cases} \tag{8}$$

As seen in the equations above, SCA has four primary parameters: r1, r2, r3, and r4. The r1 option indicates the next point's area (or movement direction), which might be inside or outside the space between the solution and the destination. The r2 option determines how far the movement can be in the destination's direction or outwards. The r3 option gives the destination a random weight, enabling you to stochastically highlight (r3 > 1) or de-emphasize (r3 1) its importance in determining the distance.

5. MATHEMATICAL PROBLEM OF GENERATION SCHEDULING PROBLEM

The unit commitment problem's objective function is displayed as a total fuel cost minimization problem, which includes fuel cost starting and shutdown costs.

$$NFC = \min \sum_{i=1}^{j} \sum_{h=1}^{t} \left\{ C(P_{i,t}) * \delta_i^t + SU(i,t)\left(1-\delta_i^t\right) * \delta_i^t + SDC(i,t) * \delta_i^{t-1} * (1-\delta_i^t \right\} \tag{9}$$

$$\forall\, i \in j; h \in t; and\ \delta_i^h \in \left\{0,1\right\};$$

$$FC_i^h = a_i + b_i * \left(P_i^h\right) + c_i \left(P_i^h\right)^2 \tag{10}$$

Where $a_i, b_i\ and\ c_i$ are the cost coefficient of $i^{th}\ unit$

The cost of starting a unit is determined by the temperature. Unit startup cost would be different if units start with cold, warmth or hot. The cost of bringing the heat producing unit online is known as the start-up cost. It is indicated in terms of the amount of time the unit has been turned off (in hours). Shut down costs, on the other hand, are a set sum for each shutting unit. Startup costs can be stated mathematically as[45]

$$SU_i^h = \begin{cases} SU_i^{hot} & if\ T_i^{MDT} \leq T_i^{off} \leq T_i^{MDT} + T_i^{cold} \\ SU_i^{cold} & if\ T_i^{off} \leq T_i^{MDT} + T_i^{cold} \end{cases} \tag{11}$$

5.1. Maximum and Minimum Operating Limits of Generators

Maximum or minimum power generation level, of each unit has unique value. Above and below deviation from that value is not desirable to create optimum electricity. The power or power generating limit is always between specified minimum and maximum power limits. This limit varies depending on the unit.

$$P_{i\bar{h}}^{\min} \leq P_h^i \leq P_{i,\bar{h}}^{\max} \qquad (i = 1,2,...,NG; \quad h = 1,2,...,H) \tag{12}$$

5.2. Power Balance Constraints

Since load demand at each hour must be balanced by power generation. All participating units whose status are marked "on" or "off" multiplied with their power generation equals to maximum load demand of that hour.[1] As expressed in following equation

$$\sum_{i=1}^{NG} P_i^h * u_i^h = P_D(h) \tag{13}$$

5.3. Spinning Backup Restrictions

Due to the prominence of reliability, there is a supply of surplus generating capacity that is necessary to respond immediately in the event of a breakdown of an already operational unit or a rapid rise in load demand. Spinning Reserve is the term for the extra generating capacity, which is calculated as:[46]

$$\sum_{i=1}^{NG} P_i^h * u_i^h \geq P_D(h) + SR(h) \tag{14}$$

5.4. Minimum-up Time Constraint

Once a unit is underway up, it has to be maintained to certain minimum time mathematically expressed as:[47]

$$T_{i,h}^{ON} \geq T_i^{MUT} \tag{15}$$

5.5. Minimum-down Time Constraint

Unit may allow to cool down certain definite time before starting again. Because each unit may take certain minimum time to fully shutdown.[48]

Mathematically expressed as:

$$T_{i,h}^{off} \geq T_i^{MDT} \tag{16}$$

6. SOLUTION APPROACH FOR GENERATION SCHEDULING PROBLEM USING SSD-SCA

This strategy employs a hybrid SSD_SCA method to exploit and explore their position in a suitable search space while keeping all restrictions in mind. The state of committed units must be understood before addressing a scheduling issue. The steps well illustrated by below flow chart

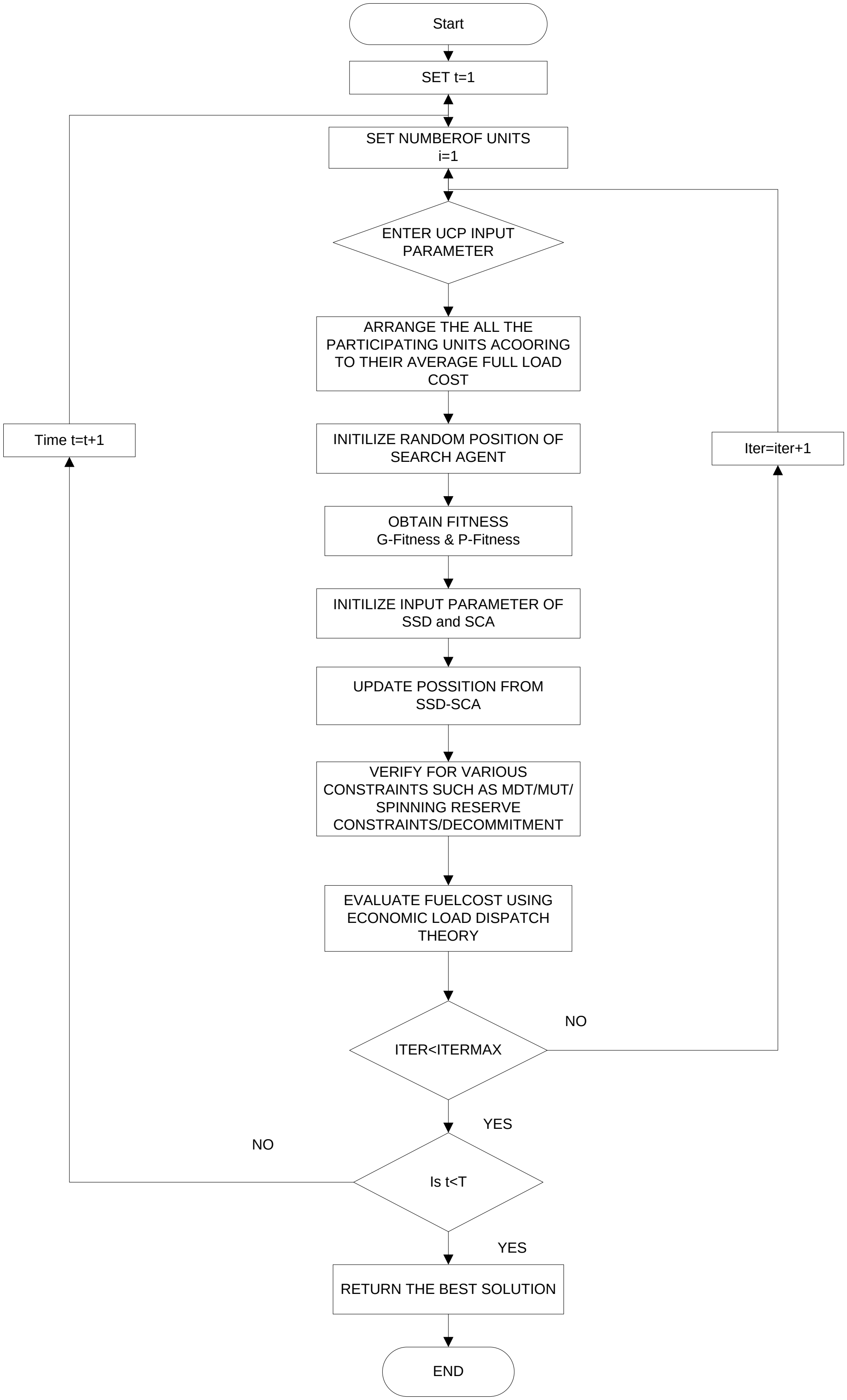

FIG (2): Flow chart of Generation Scheduling Process

7. RESULT AND DISCUSSION

7.1 Test System- 5-Generating Unit System (Thermal) With 10%Spinning Reserve

The given test system consist of 5-Generating units of IEEE-14 BUS SYSTEM having a 24-hour load demand. The SSD-1 algorithm is performed for 250 iterations and the results of given algorithm are matched with results from other algorithms for same test system. The convergence cost curve of test system is given in figure-3. The UC solution for given generating unit system is shown in table-1 that shows the optimal total operating cost is **9059.956$**. Best cost, average cost, worst cost, standard deviation, median and wilcoxon_p values are recorded as below

Best Cost	Average cost	Worst cost	Standard deviation	Median	Wilcoxon_p
9059.95615	9059.95615	9059.95615	0	9059.956	1

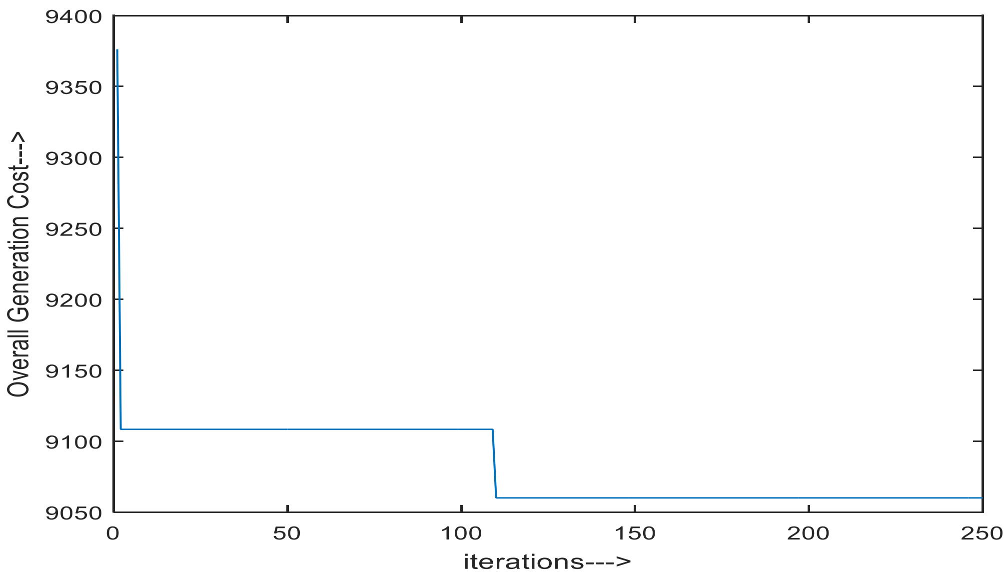

Fig (3): Convergence Curve for 5 unit Thermal Generation Units with 250 iteration

Table 1: Generation scheduling for 5 unit system (Thermal)

HOUR/UNIT	U1	U2	U3	U4	U5
1	148	0	0	0	0
2	173	0	0	0	0
3	220	0	0	0	0
4	144	0	100	0	0
5	159	0	100	0	0
6	108	140	0	0	0
7	87	140	0	0	0
8	202	0	0	0	0
9	176	0	0	0	0
10	134	0	0	0	0
11	100	0	0	0	0
12	130	0	0	0	0
13	157	0	0	0	0
14	168	0	0	0	0

15	195	0	0	0	0
16	225	0	0	0	0
17	104	140	0	0	0
18	101	140	0	0	0
19	90	140	0	0	0
20	210	0	0	0	0
21	176	0	0	0	0
22	0	57	100	0	0
23	0	38	100	0	0
24	0	103	0	0	0
				Best cost	**9059.956**

7.2 Test System- 6 -Generating Unit System With 10%Spinning Reserve

The given test system consist of 6-Generating units of IEEE-30 BUS SYSTEM having a 24-hour load demand. The SSD-1 algorithm is performed for 250 iterations and the results of given algorithm are matched with results from other algorithms for same test system. The convergence cost curve of test system is given in figure-4. The UC solution for given generating unit system is shown in table-2 that shows the optimal total operating cost is **13489.94$**. Best cost, average cost, worst cost, standard deviation, median and wilcoxon_p values are recorded as below Best cost, average cost, worst cost, standard deviation, median and wilcoxon_p for Test System 6-Generating unit's system for 24 hours' load demand (using SSD-1 algorithm)

Best cost	Average cost	Worst cost	Standard deviation	Median	Wilcoxon_p
13489.94	13489.94	13489.94	0	13489.94	1

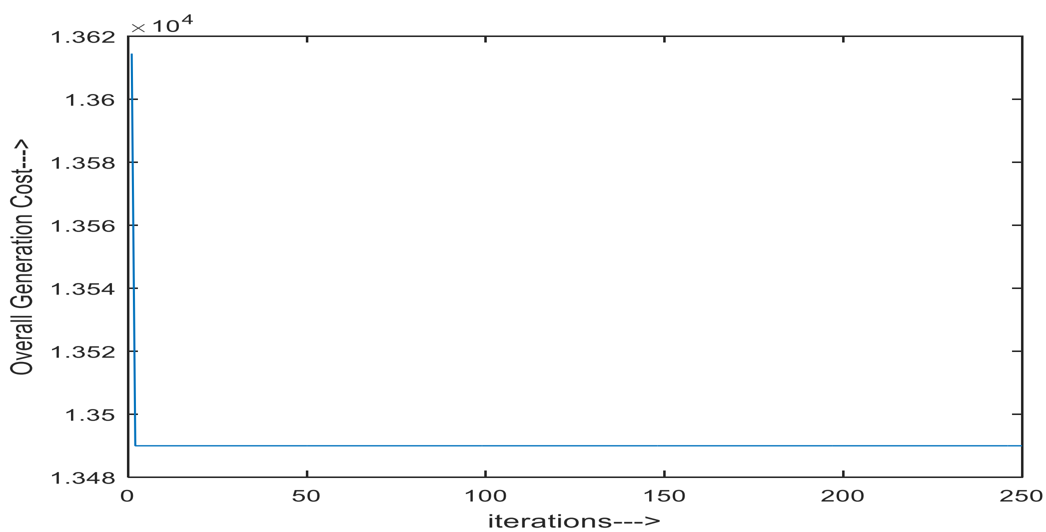

Fig 4: Convergence cure for 10-unit system

Table (2): Generation Scheduling of for 5-unit Thermal Generation Units

HOUR	U1	U2	U3	U4	U5	U6
1	166	0	0	0	0	0
2	154.3529	41.64706	0	0	0	0

3	181.5294	47.47059	0	0	0	0
4	196.5247	50.68386	19.79148	0	0	0
5	200	60.78125	22.61875	0	0	0
6	200	51.875	20.125	0	0	0
7	195.5294	50.47059	0	0	0	0
8	168.3529	44.64706	0	0	0	0
9	151.0588	40.94118	0	0	0	0
10	161	0	0	0	0	0
11	147	0	0	0	0	0
12	160	0	0	0	0	0
13	170	0	0	0	0	0
14	145.2941	39.70588	0	0	0	0
15	164.2353	43.76471	0	0	0	0
16	184	48	0	0	0	0
17	195.5294	50.47059	0	0	0	0
18	191.4118	49.58824	0	0	0	0
19	187.2941	48.70588	0	0	0	0
20	178.2353	46.76471	0	0	0	0
21	160.9412	43.05882	0	0	0	0
22	142.8235	39.17647	0	0	0	0
23	161	0	0	0	0	0
24	131	0	0	0	0	0
					Best cost	**13489.94**

7.3 Test System 7-Generating Unit System Spinning Reserve

The given test system consist of 7-Generating units of IEEE-56 BUS SYSTEM having a 24-hour load demand. The SSD_SCA algorithm is performed for 250 iterations and the results of given algorithm are matched with results from other algorithms for same test system. The convergence cost curve of test system is given in figure-5. The UC solution for given generating unit system is shown in table-3 that shows the optimal total operating cost is **34245.74244$**. . Best cost, average cost, worst cost, standard deviation, median and wilcoxon_p values are recorded as below

Best cost	Average cost	Worst cost	Standard Deviation	Median	Wilcoxon_p
34245.74244	34245.74244	34245.74244	0	34245.74	1

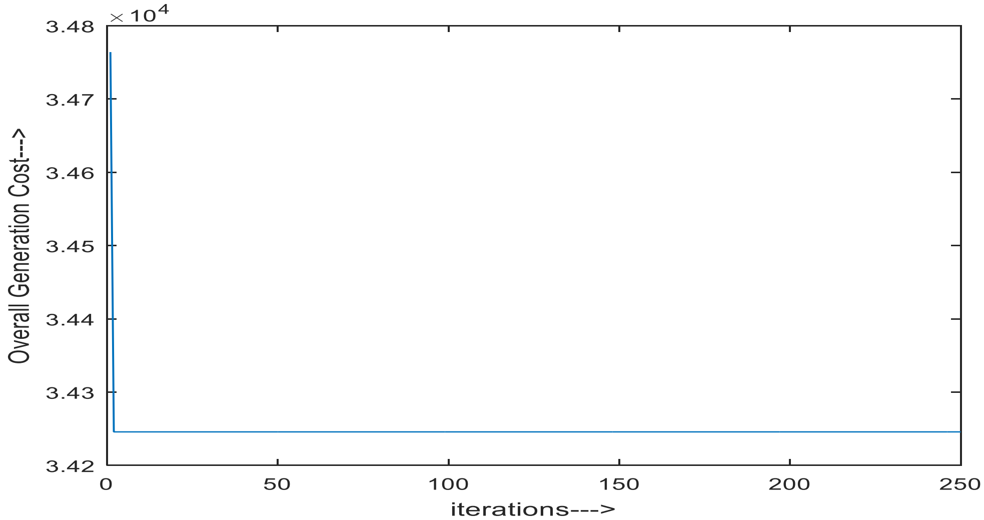

Fig (5): Convergence Curve for 5 unit Thermal Generation Units

Table 3: Generation scheduling for 7 unit system

HOUR/UNITS	U1	U2	U3	U4	U5	U6	U7
1	500	0	0	0	40	0	0
2	576	0	0	0	44	0	0
3	576	0	0	0	378	0	0
4	576	0	0	0	420	0	30
5	576	0	0	0	426	0	0
6	576	0	0	0	416	0	0
7	576	0	0	0	402	0	0
8	576	0	0	0	380	0	0
9	576	0	0	0	366	0	0
10	576	0	0	0	346	0	0
11	576	0	0	0	326	0	0
12	576	0	0	0	175	0	0
13	576	0	0	0	75	0	0
14	548	0	0	0	40	0	0
15	562	0	0	0	40	0	0
16	576	0	0	0	192	0	0
17	576	0	0	0	300	0	0
18	576	0	0	0	287	0	0
19	576	0	0	0	267	0	0
20	576	0	0	0	226	0	0
21	576	0	0	0	208	0	0
22	576	0	0	0	126	0	0
23	576	0	0	0	116	0	0
24	576	0	0	0	69	0	0
						Best cost	**34245.74**

CONCLUSION AND FUTURE SCOPE:

This study provides a hybrid algorithm that combines two meta-heuristic algorithms: the Social Sky Driver algorithm and the Sine Cosine algorithm. The proposed hybrid algorithm was created by successively passing on several places. Their own optimizer is permitted to adjust the initial random location**.** As a result, the final updated location is the result of both SSD SCA optimizers. The proposed hybrid optimizer SSD SCA is used to handle the generation scheduling issue, which is connected with a variety of inescapable variable bounds that are characterized as equality and inequality constraints. The performance of the hybrid optimizer has been tested with a wide range of units, including small thermal units with 5, 6, and 7 thermal producing units. This technique may be expanded to handle problems including both economic and environmental dispatch. It may also be used to tackle a variety of real-world engineering optimization design problems as well as restricted optimization problems.

Conflicts of Interest: "The authors declare that they have no conflicts of interest to report regarding the present study."

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Appendix A. Example of appendix

Authors that need to include an Appendix section should place it after the References section. Multiple appendices should all have headings in the style used for above. They should be ordered as such: A, B, and C etc.