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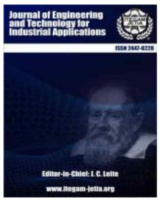

RESEARCH ARTICLE OPEN ACCESS

SOLVING THE UNIT COMMITMENT PROBLEM OF 10-GENERATORS SET BY PSO WITH DIFFERENT SPINNING-RESERVE VALUES OBTAINED FROM HOUR-HOUR LOAD DEMAND INCREASING

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ABSTRACT

Regarding energy efficiency, the unit contract problem (UCP) is significant. It need to be seen as the assurance of occasions and energy commodities in which the generator offers the most value in addition to having a large amount of energy storage. In this study, we offer a novel approach to solve the UCP issue for a 10-generator test system with variable prices depending on hourly variations in power demand, utilizing particle swarm optimization (PSO). The objective is to keep energy levels sufficient to fulfill demand while reducing the total cost of producing power. Initially, a collection of objects that may hold the key to solving UCP are generated via the suggested PSO technique. Their dedications to the project and the power they create have an impact on everyone's health because of the mobility restriction. Using a combination of their own and other objects' histories, objects may discover the best solution for UCP via the iterative adjustments in speed and location made by the PSO algorithm. This strategy might boost generator economy and efficiency while also resolving the UCP issue. A number of scenarios with various storage factors should be taken into account in order to assess the PSO method's efficacy. The results demonstrate that the cost-confidence ratio is regarded as equal and that the algorithm may converge to the ideal or nearly optimal solution. The efficiency of alternative optimization techniques and the suggested PSO approach are compared using comparative analysis. The findings demonstrate that PSO is more cost-effective than earlier research in identifying the effects of rising storage prices on power consumption between 50 and 100 MW.

I. INTRODUCTION

In order to fulfill energy demand while lowering overall production costs, generators must cooperate effectively for the electric power system to function efficiently. This issue is resolved by the Contract issue (UCP), which works out the optimal generator scheduling strategy, taking into account their obligations (on/off) and the locations where they can reliably provide power. The intricate issue of UCP has a direct bearing on energy planning. However, these approaches struggle to handle the scenario's complexity and the problem's complexity, particularly when it comes to the requirements of the fans and other challenges, which is a unique circumstance. They often resolve challenging optimization issues. The Particle Swarm Optimization (PSO) algorithm is one of the PSO algorithms; it is inspired by the behavior of swarms of fish or birds. PSO provides an effective approach to a wide range of optimization issues, including electrical system-related ones. Repurposing garbage is the new way of solving this issue. The goal is to lower the overall cost of manufacturing while still adhering to the spinning specifications in order to boost productivity and dependability. The strategy aims to address issues with energy efficiency while addressing the drawbacks of conventional methods and offering workable, efficient alternatives. Numerous research studies have looked at PSO's potential for power optimization and have shown that it may be used to handle a wide range of energy production-related issues, such as budgetary allocation, energy efficiency, and energy management. By taking into account the impact of valves, Lee et al. [1] used PSO to address the transmission issue. The results demonstrated the superiority of this strategy over others. [2] Used PSO to effectively resolve multi-objective issues that take into account both environmental and economic goals at the same time. The results demonstrate that PSO is capable of resolving competing goals and offering many Pareto-optimal options. In a different research, Hu et al. [3] used PSOs to reduce power loss and provide consistent power, hence controlling voltage and power loss in power distribution.

Additionally, PSO advancements have spawned a number of variations and hybrid strategies. Kennedy and Eberhart's objective [4] was to apply the idea of adaptive inertia to PSO; this weight accelerated the concept's convergence and preserved equilibrium between exploration and exploitation. Furthermore, combining PSO with other optimization techniques has shown promising results. For example, Wang et al. suggested a hybrid PSO-GA method. [5] They combine the local search capability of GA with the global search capability of PSO to achieve the most efficient produced power distribution. Regarding the Unit Commitment Issue, PSO has a track record of successful investigations. For the sake of this example, Liu's team [6] used PSO to solve the UCP while accounting for the maximum rate restriction and the spinning time limits; they were able to achieve the best generator scheduling and improved system reliability. In a similar vein, Chen et al. [7] used a novel PSO method to solve the UCP with a valve-like property, and this technique showed that it could provide nearly optimum solutions.

Previous studies have shown that PSO can handle the Unit Commitment Issue for a test system consisting of ten generators with varying values for the spin reserve. The development and use of a modified PSO algorithm that takes into consideration the UCP's reserve storage needs is the paper's unique contribution. The algorithm's effectiveness is ascertained by carrying out in-depth trials and comparing the outcomes with those of other widely used optimization techniques.

II. LITERATURE REVIEW

The unit commitment issue is to determine the power settings of committed units that have to abide by the regulations of both the producing unit and the system, as well as the states (on/off) of power generating units for each time slot. Minimizing the total operating cost within the given time range is the aim of the UC problem. As a result, the total of the fuel and equipment starting costs for the generating units becomes the goal function. The UC issue has the following mathematical explanation:
Reduce TC, which may be found by:

$$\sum_{i=1}^{N}\sum_{t=1}^{T}[I_i(t)F_i(P_{Ti}(t))+S_i(t)(1-I_i(t-1))I_i(t)] \quad (1)$$

the fuel cost of unit i at time t is provided by $F_i(P_{T_i}(t))$, where N is the number of generators, T is the total scheduling hours, $P_{T_i}(t)$ is the power production of unit i at time t, and li(t) is the ON/OFF state of unit i at time t (ON ndOFF=0).

$$F_i(P_{T_i}(t)) = a_i + b_i P_{T_i}(t) + c_i P_{T_i}(t)^2 \quad (2)$$

where ai, b, and c stand for unit I's fuel cost coefficients.

(t) At time t, what is the initial investment needed for unit I, as mentioned?

$$S_i(t) = \{^{S_{hi}}_{S_{ci}}\, if T_{i,off}(t) \le T_{i,Down} + T_{i,cold} if T_{i,off}(t) > T_{i,Down} + T_{i,cold} \quad (3)$$

Where is the hot starting price? TiDown is the least amount of time spent down, Ticold is the cold start time of unit i, Sci is the cold starting cost, and t is the continuous length of time off of unit i at time t.

1) System real power balance

$$\sum_{i=1}^{N} I_i(t)P_{T_i}(t) = P_i(t) \quad (4)$$

The system power demand at time t is represented by Pt(t).

2) System spinning reserve requirement

When the power grid sends a signal, the reserve version of the generator, known as Spinning Reserve, is prepared to start generating. This may happen in a matter of minutes. The service description fits the profile of most thermal generating assets (coal plant, for example), which need several hours to "warm up" and start producing. Consequently, this process pays generators that are set to spin reserve to use fuel in a "hot standby," spinning, and ready to swiftly align and create.

$$\sum_{i=1}^{N} I_i(t)P_{T_i}^{max} \ge P_l(t) + P_R(t) \quad (5)$$

The system spinning reserve at time t is denoted by $P_R(t)$.

3) Generation unit's limits

$$P_{T_i}^{m\in}(t) \le P_{T_i}(t) \le P_{T_i}^{max} \quad (6)$$

where the lowest and maximum production limits of unit I at time t are, respectively, represented by n(t) and Pmax(t).

4) Minimum up/down times

$$(T_{i,on}(t-1) - T_{i,Up})(I_i(t-1) - I_i(t)) \ge 0 \quad (7)$$
$$(T_{i,off}(t-1) - T_{i,Down})(I_i(t-1) - I_i(t)) \ge 0$$

(t) represents unit i's continually on time.

5) Ramp up and ramp down rates:

$$P_{T_i}(t) - P_{T_i}(t-1) \le UR_i \quad (8)$$
$$P_{T_i}(t-1) - P_{T_i}(t) \le DR_i$$

where URi and DRi, respectively, stand for the ramp up and ramp down rates of unit I.

III PSO-BASED METHODOLOGY

Kennedy and Eberhart developed the particle swarm optimization method [8], [9], a heuristic optimization technique that is based on social psychology. It has been noted that PSO works well with problems that have high dimensionality, numerous optima, differentiability threshold, or nonlinear. Evolution has shown that it is efficient. Compared to other optimization techniques, it offers a number of advantages, including being easy to use and potentially producing a high-quality solution with a steady tendency to converge.

Other evolutionary computational techniques modify the individual by using evolutionary operators. Nevertheless, PSO does not have an evolutionary mechanism for this. Rather, every entity in PSO swoops around, seeking a location that is dynamically modified according to its own flight history as well as the histories of its partners. Each person is seen as a volumeless sphere inside a d-dimensional exploratory space. Each particle keeps track of where it is in the space of issues; this is linked to its greatest level of achievement to yet. The term "pbest" refers to this figure. The total value and location of the largest gain made by any particle in the population to date is another advantageous feature of the particle swarm optimizer's global version. The gbest is the name given to this area. Particle swarm optimization is the idea of changing the velocity of each particle at each iteration to achieve its maximum and most advantageous positions. The item's velocity is enhanced by a random term that uses a random number generator to accelerate the object in the direction of its best and largest locations. In d-dimensional space, the ith particle, for instance, is represented by the formula x=(x_i1,x_i2,⋯x_id)). The documentation for the ith particle's former location is best=(pbest_i1, pbesti2..pbestid). The gbesta is the indicator of the biggest particle in each population. For particle i, the frequency of position change (velocity) is expressed as v = v=(v_i1,v_i2,⋯v_id). The current velocity and the distance from pbestid to gbestd may be used to calculate the changed velocity and location of each individual particle, as shown by the following formula:

$$v_{t,d}^{k+1} = wv_{t,d}^{k} + c_1 \times rand_1 \times (pbest_{t,d}^{k} - x_{t,d}^{k}) + c_2 \times rand_2 \times (gbest_{d}^{k} - x_{i,d}^{k}) \tag{9}$$

$$x_{i,d}^{k+1} = x_{i,d}^{k} + v_{i,d}^{k+1} \tag{10}$$

In this case, w is the inertia weight factor, C_1 and C_2 are the acceleration constants, rand1 and rand2 are the uniform random numbers between 0 and 1, xka is the current position of individual i at iteration k, pbest is the particle best of individual i, and gbest is the generation best of the group k,$v_d^{m\in n} \leq v_{i,d}^{k} \leq v_d^{max}$k is the velocity of individual i at iteration k.

The option vmax determines the extent to which areas close to the goal location and close to the current position are taken into account in the aforementioned procedures. Particles will struggle to pass through the advantageous solutions if v^{max} is too low. Particles won't have enough time to explore outside of the local solutions if v^{max} is too high. In the past, v^{max} was usually set at 10–20% of the range of variation on each dimension when using PSO. The weight of the random term that pushes each particle in the direction of their greatest and most advantageous locations is called the constant C_1. Before being reattached, the particles may travel great distances from their intended destinations when C_1 and C_2 have low values. On the other hand, high values cause a quick movement in the direction of or away from the targeted places. Because of this, the acceleration C_1 and C_2 values were often chosen to be in the range of 2.0 based on prior information. Equation (11) guarantees a proportionate balance between local and global exploration and exploitation for a range of inertia-related weights. According to the initial plan, w would gradually decline at a pace of 0.9 to 0.4. Generally, the following formula is used to calculate the inertia weight.

$$w = w_{max} - \frac{w_{max} - w_{m\in}}{1ter_{max}} \times lter \tag{11}$$

The maximum iteration number (generations) is represented by Itermax $Iter_{max}$, the current iteration number is $Iter_{max}$, and the maximum and lowest values of inertia weight are represented by W_{max} and W_{min}, respectively.

IV. SIMULATION

For the purposes of this paper, we assume that power reserve value should be proportional and enough to cover load demand increasing in range between 50 to 100 MW should be added over load demand, since 50 MW is the lowest increase in load demand (as we can notice in table-1-: increasing from hour 1 to hour 2 and hour4 to hour5) and 100MW is the highest increasing value (as in increasing from hour2 to hour3 and hour5 to hour6):

Table 1: The typical daily load requirement in hours.

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

Source: Authors, (2024).

This increasing in load demand will force the operator to respond effectively in two aspects, first: use ready spinning reserve to cover increasing in load demand and second, support spinning reserve for next hours.

For better planning, we will use PSO to solve UCP of 10Gen set regarding 6 different values of spinning reserve in range between 50-100MW (50, 60, 70, 80, 90 and 100) MW, figure -1- show the load demand and red-shaded area represent spinning reserve range between 50-100 MW.

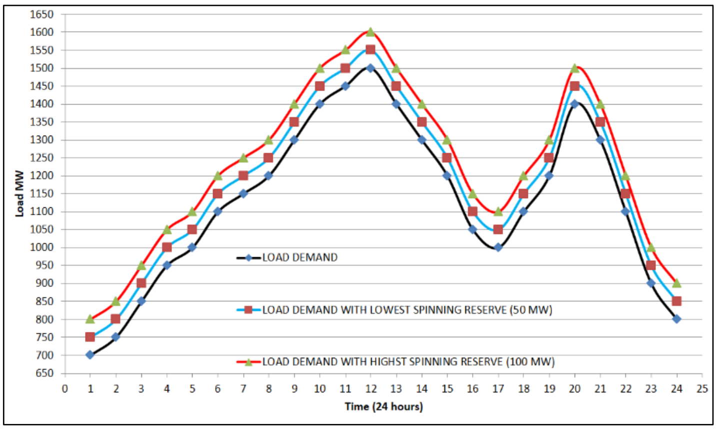

Figure 1: 24 hours load demand and spinning reserve range between 50-100 MW.
Source: Authors, (2024).

A particle's orientation may be altered by altering one of its coordinates using the binary PSO technique. On the other hand, a large number of optimizations exist in the other direction, varying in quality across levels and factors. The approach is only the change in the chance that a coordinate has a binary value (0 or 1) in the binary form of PSO [10]. Therefore, substituting equation (12) for equation (10) is the key difference between the binary PSO and the primary PSO.

$$if\,(rand < S(v_{i,d}^{k+1}))\{$$
$$x_{i,d}^{k+1} = 1$$

Else{

$$x_{i,d}^{k+1} = 1 \tag{12}$$

where S(v) is a sigmoid function that restricts the range of transformation to [0,1], and rand is a random integer selected from a uniform distribution that is limited to [0,1].

$$S(v) = \frac{1}{1+e^{-v}} \tag{13}$$

The discrete variant preserves vmax, thus $|v_{i,d}^{k+1} <$vmax|. This only reduces the final possibility that the bit xid will take on a binary value. More flexibility will be possible with a smaller vmax [11]. See [10] for further details on binary PSO.

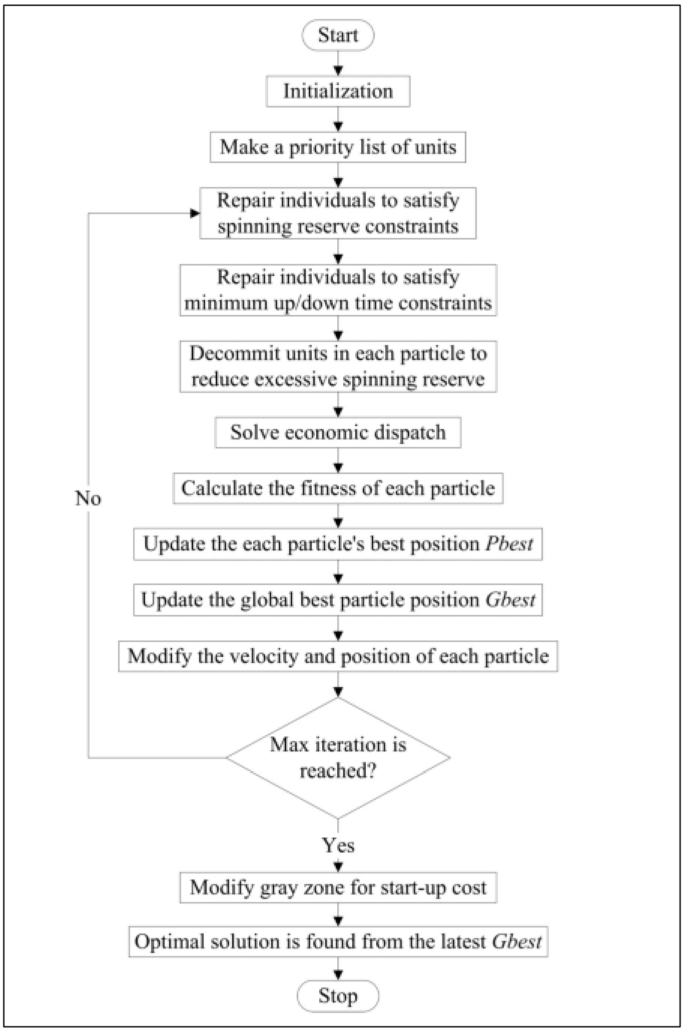

Figure 2: Binary Particle Swarm optimization for the UC problem.
Source: Authors, (2024).

A test bench with 10 units and a 24-hour timetable makes up the 10-unit system. Table (2) displays the necessary generator and data for this challenge.

Table 2: Data of the 10-Unit System.

Parameters	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
Pmax(MW)	455	455	130	130	162
Pmin(MW)	150	150	20	20	25
a($/hr)	1000	970	700	680	450
b($/MWhr)	16.19	17.26	16.60	16.50	19.70
c($/MW2hr) x10^-4	4.8	3.1	20	21.1	39.8
Min up time(hr)	8	8	5	5	6
Min down time(hr)	8	8	5	5	6
Hot start-up cost($)	4500	5000	550	560	900
Cold start-up cost ($)	9000	10000	1100	1120	1800
Cold start-up hrs(hr)	5	5	4	4	4
Initial status(hr)	8	8	-5	-5	-6
Parameters	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
Pmax(MW)	80	85	55	55	55
Pmin(MW)	20	25	10	10	10
a($/hr)	370	480	660	665	670
b($/MWhr)	22.26	27.74	25.92	27.27	27.79
c($/MW2hr) x10^-4	71.2	7.9	41.3	22.2	17.3
Min up time(hr)	3	3	1	1	1
Min down time(hr)	3	3	1	1	1
Hot start-up cost($)	170	260	30	30	30
Cold start-up cost ($)	340	520	60	60	60
Cold start-up hrs(hr)	2	2	0	0	0
Initial status(hr)	-3	-3	-1	-1	-1

Source: Authors, (2024).

Results show feasible operation control on increasing pattern within economical frame and so far safe and reliable operation as in table 3:

Table 3: Six different values of spinning reserve with total operation cost at each case.

Spinning Reserve MW	Total Operation cost
50	557046.535860194
60	558043.128870206
70	558337.564043407
80	558902.236240183
90	559655.047590170
100	560968.143280082

Source: Authors, (2024).

Also, we can notice in Figure-3- an impressive behavior of total cost increasing in spinning reserve range of 60MW to 70MW which is increase in production cost get slighter comparing to increasing of total cost in range of 70, 80, 90 and 100MW.

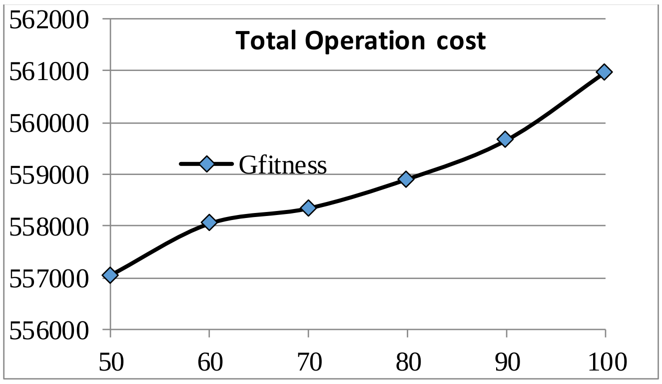

Figure 3: Total cost of units in 6 cases along with different spinning reserves values.
Source: Authors, (2024).

V. CONCLUSIONS

Simulation of PSO for 10 Generators set system using MATLAB in 6 cases represents 6 different values of spinning reserve base on load demand hour to hour minimum and maximum increasing values show magnificent results and wide reduction in cost of operation comparing with results obtained from earlier researches [11], [10].

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Methodology: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Investigation: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Discussion of results: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Writing – Original Draft: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Writing – Review and Editing: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Resources: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Supervision: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.
Approval of the final text: Ali Sadeq Alsowaidi and Seyed Mahmoud Modaresi.

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