2023 IEEE Symposium Series on Computational Intelligence (SSCI)
Mexico City, Mexico. December 5-8, 2023

A Novel Population Optimizer for Unit Scheduling Problems in Power Systems

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***Abstract*—The unit commitment (UC) problem is the first step in power system optimal scheduling and system planning. However, the UC problem is a mixed integer optimization problem, which usually has the characteristics of high dimension, non-convex and nonlinear. Plug-in electric vehicles (PEVs) integration into the grid can help improve stability and flexibility of the grid. However, Large-scale PEVs charging demand may put pressure on the grid and may lead to grid overloads. Recently, a competitive swarm optimizer (CSO) is proposed to settle optimization problems, which is considerably challenging in evolutionary computation. In this paper, a binary competitive swarm optimizer (BCSO) is proposed to tackle UC problems integration with PEVs. Finally, comparison experiments on economic problems with dimensionality increasing from 10 to 100 units, which confirm the competitive performance of the proposed optimizer.**

***Index Terms*—Scheduling optimization, Competitive swarm optimizer, Electric vehicles**

1. Introduction

The power system is the basis of modern human survival and development, the dramatic increase in the demand for electricity by people has a decisive impact on the global economy and the environment [1]. Carbon emissions, environmental pollution from thermal units based on fossil energy sources are becoming increasingly serious problems that seriously threaten the global climate and local ecosystems. The unit commitment (UC) problem is to select and dispatch each unit under some power system constraints to optimize the emission of pollutants and the total cost of power generation. UC problems are often considered as multi-constrained nonlinear mixed-integer optimization problems [2], due to the significant complexity, constraints, and binary conversion systems [3]. Currently, the integration of Plug-in electric vehicles (PEVs) into the power grid has become an important way to solve UC problems. PEVs can increase the diversity of energy sources and reduce dependence on traditional fossil fuel energy[4]. However, large-scale PEVs charging may increase the load on the grid, which may have an unstable impact on the power system[5].

To optimize the cost of power generation in the UC problem, traditional mathematical methods have been widely adopted such as integer programming methods [6], mixed integer programming methods [7], dynamic programming methods [8]. However, as the number of constraints on UC problems increases in practice, the problem becomes more complicated and takes longer to run. In recent years, there has been a growing interest in using meta-heuristic algorithms (MA) to solve UC problems, such as genetic algorithm (GA) [9], firefly algorithm [10], particle swarm algorithm (PSO) [11] and so on. These algorithms are mainly inspired by the logic of some common phenomena in nature and life, and are able to solve the optimal value of one or more objectives based on an iterative randomized optimization algorithm framework. However, as the dimensionality increases, these traditional MAs algorithms were not efficient methods to tackle large-scale problems, which easily tend to fall into local optima.

Cheng et al [12] proposed a competitive swarm optimizer, which can greatly balance exploration and exploitation. Through the information exchange between particles, the global optimal can be quickly found. At the same time, the competition mechanism introduces competition factors, which enhances the ability of local search and makes the algorithm more flexible. Numerous variations of the CSO algorithm have been suggested to address the economic dispatch problem with enhanced efficiency, such as orthogonal learning competitive swarm optimizer (OLCSO)[13], three-phase co-evolutionary competitive swarm optimizer(TPCSO)[14]. While numerous studies only have focused on the fixed demand loads in power system. However, there is a scarcity of research that investigates the economic implications of varying demand side loads in conjunction with optimal scheduling involving UC.

In this paper, a new power energy optimization framework is proposed to balance the integration of PEVs into the power system. Since the switch state of units is binary variables, a novel binary competitive swarm optimization algorithm is peoposed for solving large-scale UC problems. The rest of this paper is organized as follows. UC problem model and related formulas are mainly introduced in Section 2. The BCSO algorithm is proposed in Section 3. Then, experimental results and analysis are given in Section 4 to verify the effectiveness. Finally, conclusions are given in Section 5.

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2. UC Problem Formulation

According to the load demand, the optimization of the UC problem determines the overall economic benefits of the entire grid system, consisting of operating costs and environmental pollutant emissions, and can provide significant cost savings and achieve the balance between supply and demand of the system. In this section, the objective function of the UC problem is introduced, several major constraints are also considered.

2.1. The Objective function of UC problem

In the proposed UC model, the objective function typically represents the cost of generating power over a 24-hour period under normal conditions. In the UC problems, the cost of electricity generation per hour in a 24-hour period is considered independent of each other. The function F is as follows:

$$FEC = min\sum_{t=1}^{T}\sum_{j=1}^{n}(F_j(P_{j,t})u_{j,t} + ST_{j,t}(1-u_{j,t-1})u_{j,t}) \tag{1}$$

In formula 1, the function FEC represents the cost of generation power during the operation of unit, which is composed of fossil fuels cost and start-stop cost of the unit. By considering start-stop costs, the costs and losses associated with frequent start-ups and shutdowns can be reduced. $P_{j,t}$ is the amount of capacity generated by the jth unit in hour t. the switch state of the unit is denoted by $u_{j,t}$, which is described by 0 or 1.

In addition, the fuel cost function $F_j(P_{j,t})$ and the start-stop cost function $SU_{j,t}$ can be shown in 2 and 3 respectively.

$$F_{j,t}(P_{j,t}) = a_j + b_jP_{j,t} + c_jP_{j,t}^2 \tag{2}$$

$$ST_{j,t} = \begin{cases} ST_{H,j}, \; if \; MDT_j \leq TOFF_{j,t} \leq MDT_j + T_{cold,j} \\ ST_{C,j}, \; if \; TOFF_{j,t} > MDT_j + T_{cold,j} \end{cases} \tag{3}$$

where a_j, b_j and c_j represent the fuel cost parameters of the jth unit. The start-up cost of the jth unit in hour t is represented by $ST_{j,t}$ and MDT_j and $T_{cold,j}$ represent the minimum downtime and the threshold of cold start time of the jth unit, respectively. $TOFF_{j,t}$ is the time that the jth unit continues to stop working, and if this time is less than the threshold of cold start, then the start-up cost is defined as the hot start cost, denoted by $ST_{H,j}$. Otherwise, the cold start-up cost of unit, is denoted by $ST_{C,j}$.

2.2. Constraints

In the real world, the UC model usually contains some constraints, which ensures that the power generation units are scheduled in a way that maintains the balance between electricity supply and demand. In this paper, some constraints are considered such as power generation limit, power balance constraint, minimum up/down-time limit and so on.

1) *power balance constraint*

The generating output power of the unit should be balanced with the load demand of the system to maintain the safety of power system. The power balance constraint is as follows:

$$\sum_{j=1}^{n}P_{j,t}u_{j,t} = P_{D,t} + P_{PEV,t} \tag{4}$$

where $P_{D,t}$ represents the power demand of the load at each hour, and $P_{PEV,t}$ represents the load power of PEVs.

2) *generation constraint of UC*

According to the actual generating capacity of the corresponding unit, the output power of the unit is limited to a fixed range to ensure the normal operation of the unit. The upper and lower limit of units is shown formula 5:

$$u_{j,t}P_{j,min} \leq P_{j,t} \leq u_{j,t}P_{j,max} \tag{5}$$

where $P_{j,max}$ is the maximum generating capacity of the jth unit at hour t, and $P_{j,min}$ is the minimum generating capacity of the jth unit at hour t.

3) *Minimum up/down-time of units*

In the power system, the state of the unit is the switch variable, which has two states of "0" and "1". And both states are associated with minimum up/down time constraints. "0" means the unit is in shutdown state, and "1" means in working state. The constraint is as follows:

$$u_{j,t} = \begin{cases} 1, & if \; 1 \leq TON_{j,t-1} < MUT_j \\ 0, & if \; 1 \leq TOFF_{j,t-1} < MDT_j \\ 0 \; or \; 1, & otherwise \end{cases} \tag{6}$$

where $TON_{j,t-1}$ represents the continuously starting up time of the jth unit and $TOFF_{j,t-1}$ is the continuously shutting down time of jth unit. During the operation process, if the running time of a unit is less than the MUT_j in the t-1 time period, the unit should still keep working at the next time t, that is, set to "1". If the shutdown time does not reach the MDT_j, the unit cannot be turned on in the next time period.

4) *constraints of PEVs*

The load of PEVs is connected to the grid in this paper, so the constraints of electric vehicles need to be considered. The maximum charge and discharge power constraint and the charge load balance constraint of PEVs are shown in formulas 7 and 8 respectively:

$$P_{PEV,t,max} \leq P_{PEV,t} \leq P_{PEV,t,max} \tag{7}$$

$$\sum_{t=1}^{T}P_{PEV,t} = P_{PEV,total} \tag{8}$$

Equation 8 demonstrates that all PEVs need to be fully charged for one day of normal operation.

3. Methodology

The PSO algorithm has been extensively utilized for tackling a diverse range of optimization problems. However, when faced with large-scale optimization problems, the traditional PSO algorithm tends to fall into local optimum, thus failing to obtain ideal results. In CSO algorithm, particles compete with each other, and particles with better fitness values have a higher chance of winning the competition and influencing other particles. This competitive mechanism can enhances exploration and exploitation abilities.

3.1. CSO Optimization Algorithm

Firstly, calculate the fitness value of all particles and sort them in ascending order. The competitive mechanism of CSO is defined as follows:

$$v_{f,j}(t+1) = r_1 v_{f,j}(t) + r_2 \Delta x_{1,j}(t) + \phi r_3 \Delta x_{2,j}(t) \tag{9}$$

$$x_{f,j}(t+1) = x_{f,j} + v_{f,j}(t+1) \tag{10}$$

where $x_{f,j}(t)$ is the position of the jth particle from the ith level, and $v_{f,j}(t)$ is the velocity of the particle. $\Delta x_{1,j}(t)$ and $\Delta x_{2,j}(t)$ represent what the competitive failure particle learn from successful particle to update its position, and the formulas can be shown as follows,

$$\begin{cases} \Delta x_{1,j}(t) = x_{s,k}(t) - x_{f,j}(t) \\ \Delta x_{2,j}(t) = \bar{x}_k(t) - x_{f,j}(t) \\ \phi = 0.01 \times \frac{n}{m} \end{cases} \tag{11}$$

where $x_{s,k}(t)$ and $x_{f,j}(t)$ represent the successful and failure particle from competition respectively at hour t. $\bar{x}_k(t)$ is the mean position of the whole population. r_1, r_2 and r_3 are all parameters randomly selected from 0 to 1. ϕ is a control influence factor. The particle update the velocity and position using the competitive updating mechanism, which can maintain diversity of the population.

3.2. Binary Conversion of Decision Variables

Given that the state of unit has only two modes, on and off. This paper proposes a Binary competitive swarm optimizer (BCSO), which utilize a v-shaped transfer function to convert the parameters to 0 or 1, as shown in the following formula:

$$S(v_{f,j}) = 2 * |\frac{1}{1+e^{-v_{f,j}}} - 0.5| \tag{12}$$

From 12, it can be seen that whether the parameters are converted to 0 or 1 is determined by the speed of the particle. And the formula of the update position is shown as follows:

$$x_{f,j} = \begin{cases} 1, & \text{if } rand < S(v_{f,j}) \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where $rand$ is a random parameter ranging within [0,1]. If $S(v_{f,j})$ is greater than $rand$, the position of the particle is set to 1, which means the unit is on at this time.

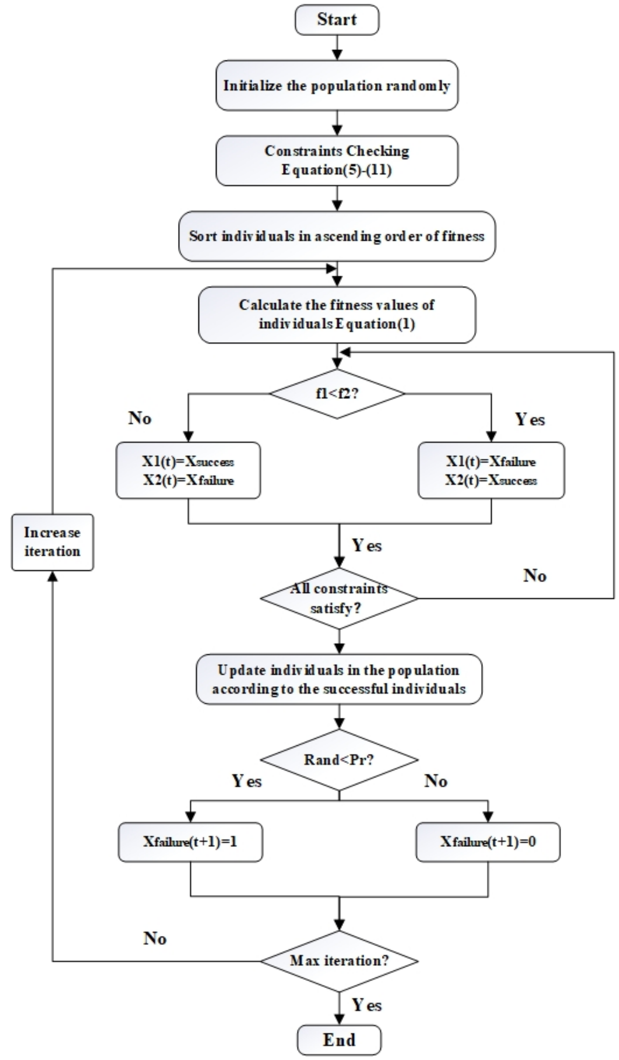

Figure 1: BCSO algorithm.

3.3. Specific Steps of BCSO

The BCSO algorithm framework is shown in Fig. 1, and the optimization process of the power energy system is as follows:

step 1 Some major parameters of generation units in power system should be set such as fuel cost coefficients of the unit, the load demand, generation capacity, maximum number of iterations and so on, and the parameters of BCSO are also initialized.

step 2 Initialize the population size, and the individuals in the population are evaluated based on the imposed constraints. Any individual that fail to meet the constraint requirements are handled using the approaches in [15].

step 3 Calculate fitness values of all individuals and rank them in ascending order according to fitness values.

step 4 Two particles compete with each other to select winners and losers, the losers update the position according to the learning mechanism above.

step 5 Judge whether the maximum number of iteration is satisfied, if not, return to the step 3, otherwise end the iteration and output the result.

4. Experimental Results and Analysis

In order to effectively verify the competitiveness and feasibility of the CSO algorithm, several different algorithms are adopted to compare with CSO in this paper. At the same time, different numbers of units are used to analyze the performance of CSO, so as to judge whether it is suitable for solving large-scale optimization problems.

4.1. Parameter Initialization

The software and hardware facilities for all experimental results are: Matlab R2022b, 8-core 4.8GHz processor, 32GB RAM. The dimension is determined by the number of units and will increase as the number of units increases. The population size of all algorithms was set to 100, and the maximum number of iterations was 200. Each algorithm is run independently 30 times to ensure randomness.

4.2. Results and Analysis

This paper compares BCSO with some other popular PSO variants, such as BPSO, BLPSO and NBPSO. The CSO algorithm takes into account the behavior of the most successful particles in the current swarm, and uses this information to update the other particles' positions and velocities, which can further improved the diversity.

The experimental economic costs obtained by the four algorithms in the case of 10-100 units is shown in Table1. From the comparison of the optimal costs, obviously, as the dimension increases, the performance of the BCSO algorithm is better than the other three algorithms. For example, when the number of units is 100, the problem dimension is 2400, and the optimal value of the objective function of the BCSO algorithm is 10532931.32 ($/day), which is at least 100000$ lower than the optimal value obtained by other algorithms. Therefore, it can be fully demonstrated that applying BCSO algorithm to UC problems has significant economic benefits compared with other similar algorithms.

TABLE 1: Simulation results comparison between different algorithms ($/day).

Methods / Units	BCSO	BPSO	BLPSO	NBPSO
10	**647097.73**	660232.42	656059.77	659405.81
20	**1313115.53**	1361712.85	1365531.02	1350198.56
40	**2932930.69**	2954532.56	2946320.31	2955941.96
60	**5031276.71**	5081598.26	5120236.23	5116523.59
80	**7642523.61**	7735412.70	7764308.78	7690234.56
100	**10532931.32**	10661547.12	10701986.46	10694520.02

The optimization results of BCSO and other algorithms is shown in Fig.2. The figure displays the convergence

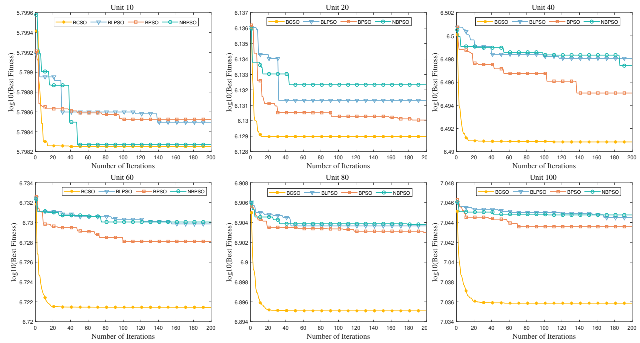

Figure 2: Convergence results of different algorithms with different unit numbers.

curves of the BCSO algorithm as it progresses through the iterative process, using problem instances with 10, 20, 40, 60, 80, and 100 units. From six cases, the yellow line represents BCSO algorithm, and there is a large gap between other algorithms, which means that the convergence speed of BCSO is faster than the other algorithms, and the BCSO algorithm show the great performance to tackle the incorporation of PEVs and the power system.

Furthermore, when the number of units is 10, BCSO converges much faster than BLPSO, BPSO and BCSO with better solutions simultaneously. And BLPSO is better than BPSO and BCSO. Since the level-based learning strategy of BCSO can improve the diversity, so that premature convergence and stagnation can be avoided. When the number of units increases to 100, the BCSO still achieves better performance than other algorithms with regard to convergence speed and optimization quality. But BCSO shows greater performance than BLPSO and BPSO, which indicates that the strategy of directly learning from better particles is suitable for large-scale optimization problems.

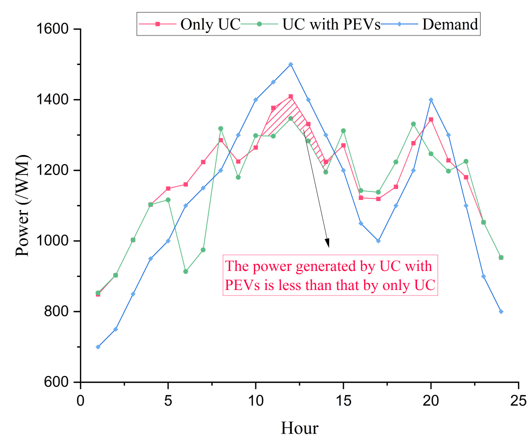

Figure 3: Compare of unit generation power in different cases.

Fig.3 shows the results of comparing the power generated by the units with or without the PEVs, and it is clear from the figure that the integration of the PEV makes the power generated by the unit more balanced. At the peak of demand at 12:00 pm, the generation power of the unit is significantly less than that without PEVs. Therefore, it is proved that the proposed scheme can significantly ease the demand pressure on the grid and balance the energy mix to make the grid more stable.

Overall, this competitive strategy may can trigger competition among individuals to exclude inferior solutions and retain superior solutions, which helps the algorithm to jump out of the local optimal and better search for the global optimal. All these results demonstrate that the BCSO algorithm is highly competitive and effective for solving the unit commitment problem.

5. Conclusion

Unit commitment is an important aspect of power system optimization operation, which has always been the main optimization task of modern power system operation planning, due to the significant economic benefits . In this paper, we have proposed a binary CSO algorithm to optimize the large-scale UC problem integration with PEVs under the necessary constraints, with the goal of minimizing economic cost. The effectiveness and feasibility of the BCSO optimization algorithm is proved by the experimental analysis of the comparison of different optimization algorithms under different numbers of units. The results demonstrate that the incorporation of PEVs on the power system can effectively reduce demand pressure on grid and reduce reliance on fossil fuels.

Acknowledgments

This research is financially supported by Technology Project of China Southern Power Grid Company Limited (No. 000000KK52210002).

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