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Full-length article

A method for power suppliers' optimal cooperative bidding strategies considering network losses

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Abstract: The bidding strategies of power suppliers to maximize their interests is of great importance. The proposed bi-level optimization model with coalitions of power suppliers takes restraint factors into consideration, such as operating cost reduction, potential cooperation, other competitors' bidding behavior, and network constraints. The upper model describes the coalition relationship between suppliers, and the lower model represents the independent system operator's optimization without network loss (WNL) or considering network loss (CNL). Then, a novel algorithm, the evolutionary game theory algorithm (EGA) based on a hybrid particle swarm optimization and improved firefly algorithm (HPSOIFA), is proposed to solve the bi-level optimization model. The bidding behavior of the power suppliers in equilibrium with a dynamic power market is encoded as one species, with the EGA automatically predicting a plausible adaptation process for the others. Individual behavior changes are employed by the HPSOIFA to enhance the ability of global exploration and local exploitation. A novel improved firefly algorithm (IFA) is combined with a chaotic sequence theory to escape from the local optimum. In addition, the Shapley value is applied to the profit distribution of power suppliers' cooperation. The simulation, adopting the standard IEEE-30 bus system, demonstrates the effectiveness of the proposed method for solving the bi-level optimization problem.

Keywords: Bidding strategy, Cooperation, Network loss, Improved firefly algorithm, Hybrid optimization.

1 Introduction

With the development of power markets around the world in the late 1990s, more attention has been paid to the bidding strategies of power suppliers [1-2]. A high-priced supplier in fierce market competition may not be accepted, and an unduly lower-priced supplier may not settle for the cost of the electricity produced [3]. To make the most of supplier interests, a favorable bidding strategy should take advantage of restraint factors, such as operating cost reduction, potential cooperation, other competitors' bidding behavior, and network losses, etc.

The bidding strategies of the power market can be divided into two broad categories: [4] a price-prediction-based bidding strategy and a game-theory-based bidding

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strategy. The price-prediction-based bidding strategy [5-7] is primarily optimized based on historical data composed by historical loads and electricity prices and then evaluated to maximize profit based on the relationship between the location marginal price (LMP) and the price quotation. However, there are two disadvantages for the price-prediction-based bidding strategy. Firstly, the scope of information disclosure is limited, making it difficult to predict the LMP due to data deficiencies. Secondly, the process of profit maximization is also hard to formulate due to the lack of analyses of other competitors' bidding behavior and congestion. Consequently, the game-theory-based bidding strategy seems to be a more appropriate tool for analyzing oligopolistic markets since it focuses on the strategic interactions among suppliers [8-9].

The game-theory-based bidding strategy comprises classic game theory and evolutionary game theory. Classic game theory maximizes the suppliers' own interests based on the Nash equilibrium concept. The authors compared the competition equilibrium with the Nash equilibriums by utilizing the cost-based method [10]. It was found that surplus and unfair allocation of market interests may be obtained using the Nash equilibrium. A new framework assuming suppliers' bid as a linear supply function was developed to establish the strategic bidding of the suppliers, and a Monte Carlo method was used to solve the model of imperfect information [11]. The min-max regret model was formulated and solved using the Benders' decomposition algorithm [12]. The proposed methodology employed supply function equilibrium to model a bidding strategy among the suppliers with constrained transmission [13]. The Nash equilibrium model can also be found in the bilateral power market in which generation companies submit bids to users, which derived an efficient allocation based on a cost matrix and the users' pay vector [14]. However, classic game theory fails to automatically acquire the dynamic bidding information of other competitors. This means that their bidding behavior cannot change based on an accurate reflection of what they may learn [15]. Consequently, many optimization algorithms based on evolutionary game theory have been developed in different domains [16],[17].

Evolutionary game theory, a combination of interconnection based classical game theory and dynamic arguments such as particle swarm optimization (PSO) [18] and the genetic algorithm (GA) [19], has also been implemented to determine the bidding curve under fiercely competitive power markets. A novel algorithm, the decomposition-based PSO method, was proposed to maximize the suppliers' expected profit, in which other competitors' LMP was assumed in a sample of possible scenarios. In [18], a two-stage operation algorithm based on the Monte Carlo simulation and a refined GA was applied to dispatch energy and the spinning reserve bidding model simultaneously [19]. Nonetheless, PSO and the GA can easily create premature convergence when implementing equilibrium solutions. In addition, various literature fail to consider the cooperative existence and network loss for which the equilibrium solution can produce deviations.

To overcome the above deficiencies, this paper focuses on investigating bidding strategies in the power market. The main contributions of this paper are listed as below:

1. A new bi-level optimization model for the coalitions of suppliers is proposed. The upper model describes the cooperative relationship among suppliers, and the lower model represents the independent system operator's (ISO) optimization. The model is designed to improve the interests of all parties.

2. By considering the influence of network loss, bidding behavior may get close to satisfying the actual conditions in a well-known power market.

3. An EGA based on hybrid particle swarm optimization and the improved firefly algorithm (HPSOIFA) was developed to tackle the bi-level optimization model for coalitions of suppliers. The methodology can produce a more reliable equilibrium solution compared with traditional methods.

The paper is organized as follows. The coalition model of suppliers with and without network loss (WNL) is given in Section 2. The novel solution methodology of an EGA based on the HPSOIFA is outlined in section 3. Section 4 summarizes numerical examples using the IEEE-30 bus system [20]. Finally, conclusions are drawn in Section 5.

2 Construction of the Suppliers' Coalition Model

The suppliers' coalitions are used to study the cooperative existences in a non-cooperative environment within a fiercely competitive power market. Much research for the bidding strategies of the power market has been devoted to studying the non-cooperative game. But there are methods within a cooperative alliance of suppliers for their bidding strategies to improve their own benefits. Therefore, this paper proposes a hierarchical coalitions' model for suppliers' bidding strategies. The upper-level model is used to maximize the suppliers' profits constituted by co-suppliers and non-co-suppliers, subject to the cost constraints of each supplier and the upper and lower limits of the bidding strategy, and ultimately to obtain the value of the bidding strategy. The lower-level model aims to schedule the suppliers to minimize their overall costs where constraints are the power balance, the line flow, the electrical output, and the line flow limit, which means that the LMP of each supplier can be solved. In addition, network loss is also considered in the coalition model for the sake of the analysis of its influence on suppliers' bidding behaviors. Note that the bi-level optimization model considered here is quite different from the coalitions presented in [21]. Firstly, some constraints, such as the transmission line and network loss, are considered in this paper, but not considered in [21]. Moreover, supplier quotations in this paper exploit a piece-wise supply curve which is not the case in [21]. Finally, the proposed model in this paper aims to research dynamic equilibrium from bidding behavior and establish how best to distribute profits. However, the goal of [21] was primarily to perceive the impacts of potential coalitions.

2.1 Upper-level model

The upper-level model is used to maximize the suppliers' profits and assumes there to be cooperative suppliers in a non-cooperative environment. Hence, it is assumed that the bidding strategy of the electricity power pool constituted by suppliers I is submitted to the ISO. The structure for the suppliers' bidding behavior is shown in Fig. 1.

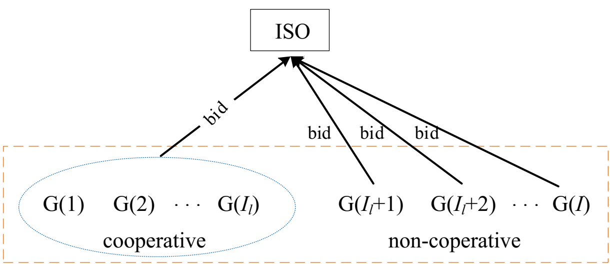

Fig. 1 Coalition model with suppliers I

In Fig. 1, where G(1), …, G(I) represent units, I_1 is selected for the cooperative bidding behavior of suppliers:max $\{f_1+f_2+,...,+f_{I_1}\}$, meaning that other suppliers I_2 (I minus I_1) are non-cooperative suppliers I_1: max $\{f_{I_1+1}, f_{I_1+2},..., f_{I_2}\}$. Therefore, the profits of suppliers I can be described as follows:

$$\max\ \{(f_1+f_2+,...,+f_{I_1}), f_{I_1+1}, f_{I_1+2},..., f_{I_2}\} \tag{1}$$

where i denotes a supplier; f_i represents profit for supplier i and can be formulated by its own income minus its own full cost, expressed as:

$$f_i = \rho_i q_i - C_i \tag{2}$$

where ρ_i and q_i are the LMP and awarded generation quantity for supplier i. The cost functions for supplier i can be formulated as follows:

$$C_i = a_i q_i^2 + b_i q_i + c_i \tag{3}$$

where a_i, b_i and c_i are the cost coefficients for supplier i. Although the bidding behavior of each supplier can choose its own cost coefficient to decide its own bidding strategy, practically it is difficult to apply for a bidding strategy because of the existence of three parameters of cost coefficient. The cost coefficient of each supplier can be transformed into the parameter k_i, as described in [13], as follows:

$$\phi_i = k_i(a_i q_i^2 + b_i q_i + c_i) \tag{4}$$

where k_i is the bidding strategy for supplier i. In general, the range of the k_i should be limited and described as follows:

$$k_i^{\min} \leqslant k_i \leqslant k_i^{\max} \tag{5}$$

where $k_i^{\min}$ and $k_i^{\max}$ are the lower and upper bound of the bidding strategy for supplier i, respectively. The bidding price of each piece-wise supply curve can be calculated, as follows, where λ_{is} represents the bidding price and w_{is} represents the bidding quantity of the sth segment for supplier i:

$$\lambda_{is} = \partial\phi_i/\partial q_i = k_i(2a_i\omega_{is} + b_i) \tag{6}$$

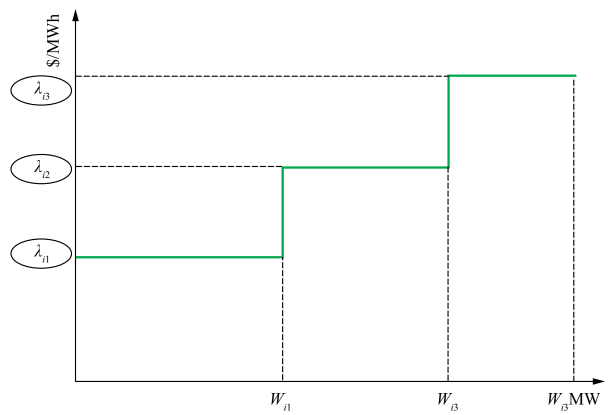

Fig. 2 Bidding curve for supplier i

By constructing the profit function and establishing the inequality and equality constraints for the suppliers' coalitions, the upper-level model can be written as a general optimization function, expressed as:

$$\begin{aligned} &\max\ \{(f_1+f_2+,...,+f_{I_1}), f_{I_1+1}, f_{I_1+2},..., f_{I_2}\} \\ &s.t.\begin{cases} g_m(x)=0 & m=1,2,...N_{eq} \\ h_j(x)\leqslant 0 & j=1,2,...N_{ieq} \end{cases} \end{aligned} \tag{7}$$

where x represents the numbers of decision variables for the upper-level model; N_{eq} and N_{ieq} are the numbers of equality and inequality constraints; g_m represents the mth equality constraint, and its corresponding equation can be found in constraints (2), (3), and (6); h_j is the jth inequality constraint, and its corresponding equation can be found in constraint (5).

2.2 Lower-level model

What is unique about the lower-level model is that the ISO is cleared according to the security constraints economic dispatch, while the bidding strategy from the upper-level model is submitted to the ISO. In addition, this paper analyzes the influence of the bidding strategy considering network loss (CNL) or without network loss (WNL).

2.2.1 Without network loss

The LMP for the WNL approach consists of the cost of margin fuel and congestion. The main advantages of this market for WNL are that it can first be applied to the optimal power flow method to deal with network congestion, and then it can reflect the unfair marginal cost of the nodal load. The model can be established by WNL, as follows:

$$\min \sum_{i=1}^{I}\sum_{s=1}^{S_i} \lambda_{is} q_{is}$$

$$\text{s.t.} \begin{cases} \sum_{s=1}^{S} q_{is} = q_i \\ \sum_{i=1}^{I} q_i = \sum_{b=1}^{B} q_b \\ T(q_i - q_b) = F_l \\ q_i^{\min} \leqslant q_i \leqslant q_i^{\max} \\ F_l^{\min} \leqslant F_l \leqslant F_l^{\max} \\ (i = 1, 2, ... I; l = 1, 2, ..., L; b = 1, 2, ..., B) \end{cases} \tag{8}$$

where L and B are the numbers of lines and buses in the power system; S_i is the number of segments for supplier i. λ_{is} and q_{is} are the bidding price and quantity for segments s of supplier i; q_b denotes the nodal load for bus b; T is the shifting factor; F_l represents the line flow on line l; $q_i^{\min}$ and $q_i^{\max}$ are the minimum and maximum output for supplier i. $F_i^{\min}$ and $F_i^{\max}$ are the lower and upper limits of real power flow on line l. In (8), the first equality constraint is the total awarded generation quantity for supplier i. The second equality constraint is the power balance constraint. The third equality and fifth inequality denote the line flow and security constraint on line l.

Once the security constrained economic dispatch (SCED) model for WNL is determined, the LMP of each supplier can be solved based on the Kuhn-Tucker condition [23], as follows:

$$\rho = \eta - T^T(\gamma^+ - \gamma^-) \tag{9}$$

where η is the Lagrangian multiplier for the power balance constraint; and γ^+ and γ^- are the forward and reverse Lagrangian multipliers for the line flow constraint. Note that it is also clear in constraint (9) that the LMP is the composition of the costs of marginal energy and congestion.

2.2.2 Considering network loss

The LMP for CNL comprises the cost of margin fuel, congestion, and margin loss. The model not only has the advantages of the model for WNL but also reflects the loss cost of the line. The model can be built by considering the network loss, as follows:

$$\min \sum_{i=1}^{I}\sum_{s=1}^{S_i} \lambda_{is} q_{is}$$

$$\text{s.t.} \begin{cases} \sum_{s=1}^{S} q_{is} = q_i \\ \sum_{i=1}^{I} q_i - \sum_{b=1}^{B} q_b - P_{loss} = 0 \\ P_{loss} = H^T\left(\sum_{i=1}^{I} q_i - \sum_{b=1}^{B} q_b\right) + \psi_l \\ T_l(q_i - q_b) = F_l \\ q_i^{\min} \leqslant q_i \leqslant q_i^{\max} \\ F_l^{\min} \leqslant F_l \leqslant F_l^{\max} \\ l = 1, 2, ..., L \\ b = 1, 2, ..., B \end{cases} \tag{10}$$

where P_{loss} denotes the system loss; H and ψ_l are the sensitivity and linearization offset in the system loss. In constraint (10), the second equality constraint is the power balance constraint; the third equality constraint represents the power loss. More detailed information regarding the above constraints for CNL can be found in [23].

Once the SCED model with network loss is cleared, the LMP of each supplier can be formulated based on the Kuhn-Tucker condition as follows:

$$\rho = \eta e - \eta \partial P_{loss} / \partial q_i + T_l^T(\gamma^+ - \gamma^-) \tag{11}$$

According to the constraint (11), it is clear that the LMP consists of three parts: the costs of marginal energy, marginal loss, and congestion.

3 Solution Method

To effectively solve the suppliers' coalition model, a novel hybrid optimization algorithm consisting of an EGA, PSO, and an IFA is proposed.

3.1 Evolutionary game theory

Evolutionary game theory, as proposed by Maynard Smith and Price in 1973, combines the research results of classical game theory and ecological theory, and takes the group of limited rational participants as the research object [24]. In addition, a dynamic analytic method is also introduced to the EGA to analyze the various influencing factors of the participants' behavior. Compared with traditional game theory, the EGA emphasizes the dynamics of strategic change rather than the nature of strategic equilibrium. Consequently, the personal knowledge, belief, and risk preference of the participants are considered in some ways. To date, the EGA has been used in a variety of practical fields [25].

In this paper, the EGA is used as the theoretical basis for market equilibrium, and the HPSOIFA is used to dynamically change bidding behavior. In the process of information interaction, each supplier is modeled and encoded as one adaptive individual, and next updates their bidding behavior from learning opponents' bidding information using the HPSOIFA, to further improve their benefits. The next section describes how the HPSOIFA updates their bidding behavior.

3.2 Hybrid particle swarm optimization and improved firefly algorithm

PSO, proposed by Dr. Eberhart and Dr. Kennedy, is a type of powerful numerical computational algorithm with limited function evaluations [26]. However, the main disadvantage with PSO, especially in dealing with the optimization of complex multi-modal functions, is its liability to produce premature convergence, which can be attributed to the loss of diversity in the search space [26]. To overcome the above problem, this paper aims to balance the tradeoff between local exploitation and global exploration. It can be seen from the above analysis that PSO may be subjected to premature convergence when particles are trapped in local minima. On the other hand, the firefly algorithm (FA) [27] that was proposed by Yang in 2008, as another computational algorithm, can be engineered to overcome this drawback, though it also has several weaknesses such as slow convergence due to the lack of knowledge of the location of the individual optimum [27]. Therefore, a novel HPSOIFA is proposed to utilize the strengths of all of these algorithms.

3.2.1 Halton initialization

A uniformly distributed initialization is generally suitable for finite sub-optimization problems when solving coalition equilibrium for the suppliers in the power market since it would not be oblivious to the optimum location. However, several studies have found that the Halton point set can produce a more uniform distribution to the entire population of space and show a high degree of regularity. Moreover, numerical calculations for the Halton point set have indicated that it may enhance the algorithm's performance [28]. Thus, the Halton point set is introduced to the initialization process, as follows:

$$\begin{aligned} &k_{i,j}^{0} = k_{i,d}^{\max} + Halton_i(i,d) \times (k_{i,d}^{\max} - k_{i,d}^{\min}) \\ &i = 1,2,\ldots,N_p; d = 1,2,\ldots,N_d \end{aligned} \tag{12}$$

where $k_{i,j}^{0}$、 $k_{i,d}^{\max}$ and $k_{i,d}^{\min}$ denote the initialized value, and the upper and lower bound of the bidding strategy for supplier i. N_p and N_d represent the population size and dimension of decision variables. $Halton_i(i,d)$ is the pseudo-random value acquired from the Halton code [28].

3.2.2 Selection

According to the above analysis, there are some advantages for the global exploration and rapid convergence in standard PSO, but from a local search perspective it is a disadvantage that can be completely remedied by the FA due to its fine-tuning controls in local exploitation. Therefore, particle updating in local exploitation will implement an FA, if particles are superior to the previous global best value, otherwise, the particle will be updated using PSO. Mathematically, the selection operator can be described as follows:

$$\theta_i^t = \begin{cases} 0 & p_i^t > g^{t-1} \\ 1 & p_i^t \leqslant g^{t-1} \end{cases} \tag{13}$$

where θ_i^t is the selection update way for the i th particle in the i th iteration. p_i^t denotes the current solution for the i th particle in the t th iteration. g^{t-1} represents the global solution in the $(t-1)$th iteration.

3.2.3 Updates by PSO

In each iteration, the particle updates itself by tracking two extremes. The first is the optimal solution found by the particle itself, which is called the individual extreme value. Another extreme value is the optimal solution found by the whole population, which is the global extreme value. Hence, population updates with PSO according to the above can be described as follows:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i^t - k_i^t) + c_2 r_2 (g^t - k_i^t) \tag{14}$$

$$k_i^{t+1} = k_i^t + v_i^{t+1} \tag{15}$$

where r_1 and r_2 are random numbers between 0 and 1; c_1 and c_2 denote learning factors; v_i^t represents the velocity vector for the i th particle in the t th iteration; w is the inertia weight that employs the variable weight method to enhance the convergence rate generally, as follows:

$$w = (w_1 - w_2)(t^{\max} - t) / t^{\max} + w_2 \tag{16}$$

where w_1 and w_2 are initial weight values; $t^{\max}$ is the maximal iteration number.

3.2.4 Updates by IFA

At each iteration, fireflies can take advantage of their attractions to update the population locations. However, the excessive existing attractions between fireflies will produce an oscillation that deteriorates the local search ability. A chaotic-sequence-based theory can assist the FA to avoid some local minima and increase the algorithm's performance. Accordingly, the update rule of fireflies can be expressed as follows:

$$k_i^{t+1} = k_i^t + r_0 e^{-\gamma r_{ij}^2} \vartheta_i^t (k_j^t - k_i^t) + a_t \xi_t \tag{17}$$

where ϑ_i^t and a_t are a time-series chaotic number and a variable step-size parameter that are calculated according to constraints (26) and (27); ξ_t is a random variable vector; r_0 denotes the initial attractiveness; k_i^t is the brighter firefly than the i th firefly; γ denotes a constant light absorption coefficient; r_{ij} is the distance between two fireflies in constraint (28) based on Euclidean theory. In addition, its previous location is applied to change the velocity correspondingly using constraint (29), as follows:

$$\vartheta_i^{t+1} = \mu(\vartheta_i^t)^2 \sin(\pi\vartheta_i^t) \tag{18}$$

$$a_t = 1 - rand^{(1-t/t^{\max})^{dr}} \tag{19}$$

$$r_{ij} = \left\|k_i - k_j\right\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{20}$$

$$v_i^{t+1} = k_i^{t+1} - k_i^t \tag{21}$$

where μ is a parameter that controls chaos behavior; and dr is the decay rate.

3.2.5 Stop

The optimization algorithm will be terminated, if the number of iterations has reached the maximum and its corresponding solution is stable, as follows:

$$t > t^{\max} \tag{22}$$

$$k_i^{t+1} = k_i^t \tag{23}$$

3.3 Solution framework

In this paper, firstly, a bi-level model for the suppliers' coalition is established and the bidding strategy of each supplier is modeled as the value k. Then, the HPSOFAEGA that is composed of an EGA and an HPSOIFA is used to solve the two-level optimization problem. Afterward, based on dynamic equilibrium by the EGA, the HPSOIFA is utilized to update their bidding strategy and obtain the Nash equilibrium in the dynamic power market. Ultimately, the profits of cooperative suppliers are distributed by the Shapley value. In conclusion, the flow chart of the HPSOFAEGA for solving the suppliers' coalition model is shown in Fig. 3.

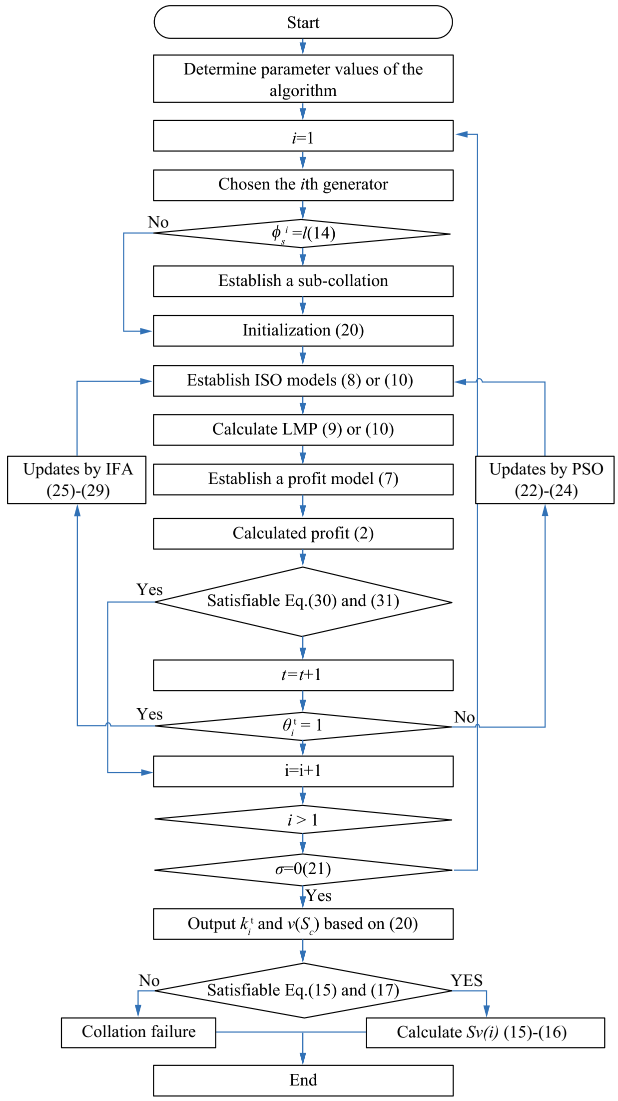

Fig. 3 Flowchart of the proposed algorithm

4 Empirical Results

4.1 Experimental settings

The standard IEEE30 bus system serves as the grid topology in the power market. The standard IEEE30 bus system consists of 24 load buses, 41 transmission lines and 6 generators (suppliers). Various academics have fully implemented the system parameters. The fuel cost coefficients, and the lower and upper bound of the power output for six suppliers are shown in Table 1. In addition, it is assumed that the bidding quantity for each segment of the bidding curve is homogenized.

Table 1 Cost parameters of suppliers

Suppliers	a	b	c	P_{max} (MW)	P_{min} (MW)
G1	0.02	2	0	25	0
G2	0.0175	1.75	0	22	0
G3	0.0625	1	0	24	0
G4	0.00994	3.25	0	28	0
G5	0.025	3	0	25	0
G6	0.025	3	0	24	0

Firstly, in the HPSOIFA, the PSO algorithm parameters come mainly from the following: the initial weight values w_1 and w_2 are fixed at 2 and the learning factors c_1 and c_2 are set to 3.1 and 2.1, respectively. Furthermore, four algorithm parameters of the IFA, such as r_0, γ, μ, and dr, are of great importance and necessity to guide the implementation for local searching ability. Here, based on analysis, r_0, (the initial attractive distance) is set to 1. The absorption coefficient, γ, determines the change of attractiveness over time. A larger value of γ would raise the instability of the algorithm and a smaller value of γ would tend to cause a slow convergence rate. Our experiments demonstrate that γ should be set at 1 in this paper. Moreover, μ is exploited to control chaos behavior and is set to 2.1. dr is required to determine the size of the decay rate and generally is fixed at 0.95. Finally, N_p and t^{max} are the numbers of the population and maximal iteration. In general, N_p should vary from 30-60, and t^{max} should be in the range 20-60. It all depends on the highly constrained and complicated problem, whose settings can influence the convergence rate. Our simulations, however, show that N_p and t^{max} should be set to 40 and 30, respectively.

4.2 Case 1: Investigations of completely cooperative bidding

To investigate the completely cooperative bidding in detail in terms of WNL or CNL, we first validate the proposed algorithm to analyze the overall optimization performance. Afterwards, a completely cooperative bidding model is simulated and analyzed.

For the above coalition, the characteristic function value is calculated in different sub-coalitions Sc, composed of S_1, S_2,…, S_{63}, which determine the Shapley value for each supplier. These cases are shown in Figures 6 and 8. In addition, sub-coalition S_{63} is selected to demonstrate the feasibility of the convergence performance for the proposed algorithm on two different occasions for WNL or CNL. This performance is evaluated using the convergence characteristic and stability compared to the FA, PSO, and the hybrid firefly and particle swarm optimization algorithm (HFPSOA). The stability of the algorithm for WNL or CNL is shown in Table 2, and the convergence characteristic are shown in Figs. 4 and 5, respectively. Note that the optimal value is the maximum due to the maximal suppliers' profits.

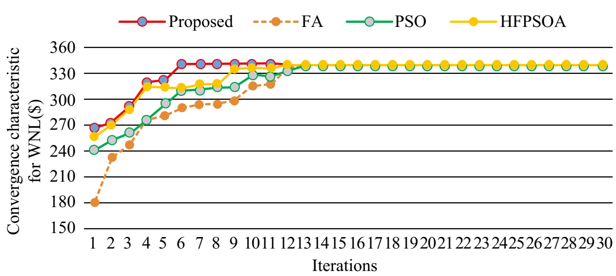

Fig. 4 The plot of convergence characteristic for WNL

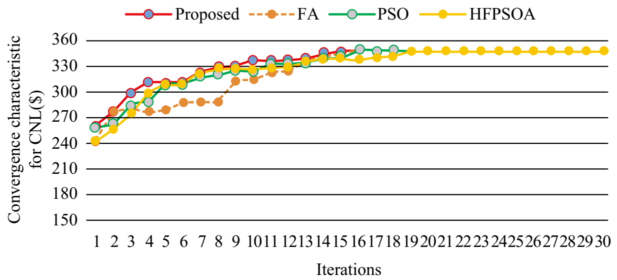

Fig. 5 The plot of the convergence characteristics for CNL

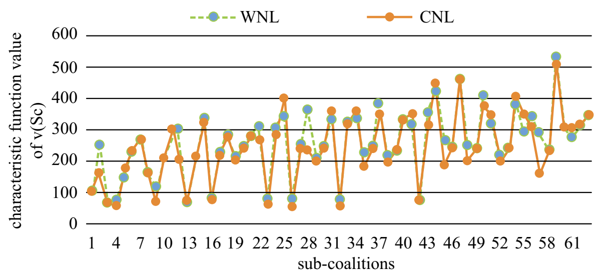

Fig. 6 Characteristic function values of v(Sc) for completely cooperative bidding

Table 2 Cost parameters of suppliers

Kind	Algorithms	Worst($)	Best($)	Mean($)	Var.
WNL	Proposed	341.2175	341.2176	341.2175	1.12E-9
G2	FA	340.5203	340.5246	340.5225	1.06E-6
G3	PSO	340.3456	340.3559	340.3507	5.60E-5
G4	HFPSOA	341.2166	341.2176	341.2171	6.53E-8
CNL	Proposed	348.4150	348.4154	348.4152	3.85E-8
G6	FA	348.2941	348.3033	348.2983	5.96E-6

When the graphs of Figs. 4-5 are analyzed, the results show that the proposed algorithm has enhanced the searching precision and the properties of fast convergence more so than with PSO, the FA, and the HFPSOA. These cases are attributed to the techniques that exploited the combination of global exploration with PSO and local exploitation with the IFA. It is especially noteworthy that the convergence characteristic of the HFPSOA was much slower than the proposed algorithm. This is because the chaotic sequence theory can restrain it from the local optimum. In addition, the results with the proposed algorithm also reveal better effects from the initiate optimization than with PSO, the FA, and the HFPSOA, as shown in Figures 4-5. This is determined by the characters of the Halton initiation that can increase the algorithm's performance.

In general, the performance of intelligent optimization algorithms, such as the FA and PSO, will vary in different simulations due to the variability of the algorithm parameters. Consequently, to verify the stability of the proposed algorithm, the proposed algorithm and contrasting methods, such as the FA, PSO, and the HPSOFA were repeated 20 times(based on experiment). For WNL, the convergences with the HPSOIFA, the FA, PSO and the HPSOFA were varied from \$341.2175 to \$341.2176, from \$340.5203 to \$340.5246, from \$340.3456 to \$340.3559, and from \$341.2166 to \$341.2176, respectively, and their corresponding variances were 1.12×10^{-9}, 1.06×10^{-6}, 5.60×10^{-5}, and 6.53×10^{-8}, respectively. For CNL, the proposed algorithm is averagely \$348.4152 converged with a variance of 3.85×10^{-8}. The average convergence of FA, PSO and HPSOFA are \$348.2983 with a variance of 5.96×10^{-5}, \$348.3989 with a variance of 5.34×10^{-5} and \$348.4115 with a variance of 9.60×10^{-7}. Therefore, these results also indicate that the proposed algorithm significantly outperformed the normal algorithms, from an accuracy and stability perspective.

From Fig. 6, the characteristic function value for completely cooperative bidding exhibits unanimity based on WNL or CNL, as expected. This is because network loss accounts for a small proportion of the total load. Meanwhile, the characteristic function of sub-coalition S63 is \$341.2 and \$348.4 for WNL and CNL, respectively, and its corresponding maximum is \$532.1 and \$504.9 located at the 59th sub-coalition. Therefore, the maximum is not P set, rather than sub-coalition S59 (composed of suppliers i.e., G1, G2, G3, G5, and G6). This shows that the profit of supplier G4 is not greater than the benefits in the individual bidding strategy and thus the coalition fails for completely cooperative bidding based on WNL or CNL.

Table 3 Optimal bidding strategy and Shapley value of each supplier for completely cooperative bidding

Type	No	G1	G2	G3	G4	G5	G6
WNL	*k*	1.70	1.25	1.48	1.40	1.81	2.00
	Sv (\$)	46.7	89.4	33.9	-59.9	100.5	130.5
CNL	*k*	1.72	1.31	1.46	1.40	1.79	2.0
	Sv (\$)	40.7	66.3	28.5	-66.5	108.5	170.7

As can be seen in Table 3, when 1.70, 1.25, 1.48, 1.40, 1.81, and 2.0 times each supplier's marginal costs, respectively, are finally selected for the bidding strategy based on WNL, the summation of all Shapley values for each supplier are \$341.2, and for CNL, when each supplier chooses to bid at 1.70, 1.25, 1.48, 1.40, 1.81, and 2.0 times their marginal cost respectively, the summation of Shapley values for each supplier is \$348.4. The results show that the bidding strategy can change slightly due to the consideration of network loss, and the sum of Shapley values for each supplier that is equal to the value of sub-coalition S63 can settle for the Pareto distribution of completely cooperative bidding. However, the profits of the supplier G4 are less than zero in both cases. This obviously does not accord to the facts, which further indicates that completely cooperative bidding may not be the best way to increase revenue.

4.3 Case 2: Investigations of partially cooperative bidding

It can be seen from the above analysis that the Shapley value of supplier G4 is a negative value for completely cooperative bidding based on WNL or CNL, which means that supplier G4 cannot cooperate with other suppliers. Therefore, suppliers (let Gg=i.e., G1, G2, G3, G5, and G6) are assumed as a coalition in this subsection, and are, hypothetically, non-cooperative with supplier G4. This case indicates that suppliers are partially cooperative while bidding for WNL or CNL. Therefore, the characteristic function value *Sc* and the Shapley value *Sv* are {*S*1, *S*2,…, *S*31}and{*Sv*1, *Sv*2, *Sv*3, *Sv*5, *Sv*6}, as shown in Figure 8 and Table 4, respectively. Meanwhile, this section builds key research insight into the bargaining game model between the supplier G4 and the suppliers Gg due to the existence of a non-cooperative game. The results in Fig. 7 show the profits associated with the dynamic equilibrium change.

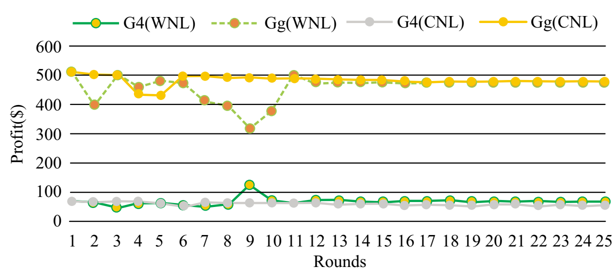

Fig. 7 Dynamic equilibrium change for G4 and Gg

In Fig. 7, it is clear from the Nash equilibrium of the power market that the profits of supplier G4 and Gg for WNL are \$67.5 and \$477.0 respectively, and the profits of supplier G4 and Gg for CNL are \$57.5 and \$478.9 respectively. In the latter case, the profits fell slightly. Hence, these results again numerically affect the suppliers' profits because of network loss. Moreover, it is clear (from the perspective of dynamic equilibrium change) that the normalized variances of supplier G4 and suppliers Gg for WNL are 0.03 and 0.05, respectively, and that the normalized variances of supplier G4 and suppliers Gg for CNL are 0.08 and 0.12, respectively. In both cases, these results suggest that profits have a negative correlation, as can be seen from Fig. 7, as there is a competitive relationship between supplier G4 and suppliers Gg with consideration of the equal load distribution. Moreover, it does not demonstrate a linear relationship for the suppliers' profits. This is because each supplier profit is not only related to the other competitors' bidding behavior but also to other factors, such as operating cost reduction, potential coalitions, and network constraints. Therefore, it suggests that the coalition can produce a cooperative surplus through cooperation or compromise between two or more parties.

Table 4 Optimal bidding strategy and Shapley value of each supplier for partially cooperative bidding

Type	No	G1	G2	G3	G4	G5	G6
WNL	*k*	1.52	0.80	1.48	1.75	1.91	1.52
	Sv ($)	75.7	127.6	51.9	67.3	154.4	75.7
CNL	*k*	1.61	1.35	1.31	1.80	1.99	1.61
	Sv ($)	61.9	109.7	48.9	82.9	174.6	61.9

It can be seen from Fig. 8 that the maximal characteristic function value for partially cooperative bidding is that of sub-coalition S31, and thus its corresponding optimal profits is the set {G1, G2, G3, G5, and G6}in both cases. Therefore, cooperative bidding can generate a cooperative surplus and represent successful cooperation for suppliers Gg. Meanwhile, Table 4 shows that when 1.52, 0.80, 1.48, 1.75, 1.81, and 2.0 times each supplier's marginal costs, respectively, were selected for the bidding strategy based on WNL, the Shapely value for each supplier was $75.7, $127.6, $51.9, $67.3, and $154.4 respectively, and for CNL, when each supplier chose to bid at 1.61, 1.35, 1.31, 1.80, and 1.99 times their marginal costs, respectively, the Shapely value of each supplier was $61.9, $109.7, $48.9, $82.9, and $174.6, respectively. In both cases, it is further evidence that network loss can affect the bidding strategy and the suppliers' profits. Furthermore, the profit of supplier G5 and supplier G6 increases, as the network loss changes their marginal contribution.

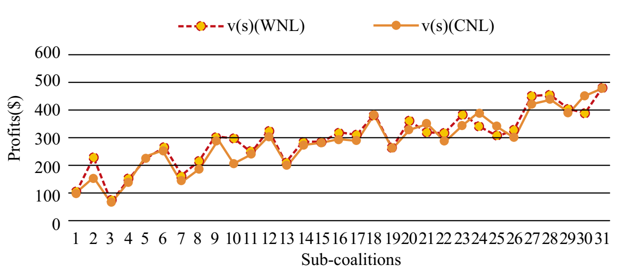

Fig. 8 Characteristic function value of v(Sc) for partially cooperative bidding

5 Conclusions

In this paper, by CNL or WNL, a bi-level model for the suppliers' cooperative bidding is proposed to enhance their profits. A hybrid algorithm combining the EGA, PSO, and the improved FA was developed to efficiently solve the bi-level model. In addition, the Shapely value was applied to the profit distribution of the power suppliers' cooperation. Finally, a HPSOIFA was comprehensively compared with reported methods, such as PSO, the standard FA, and the HFPSOA. The developed model was also synthetically analyzed by completely cooperative bidding and partially cooperative bidding under the IEEE30-bus system. The statistical results demonstrate that the proposed algorithm achieved a better solution for the function optimization problem when compared to the benchmarks. This is due to a novel strategy that adopted global exploration with PSO, local exploitation with the FA, and the chaotic-sequence-based theory. Meanwhile, the numerical results also show that the cooperative behavior of the suppliers from completely and partially cooperative bidding may increase the income of power generation companies, but there exists a risk of coalition failure. The impact of network loss on power suppliers' bidding behavior and profits was also studied. In summary, the established model and the solution algorithm demonstrated strong potential for practical implementation of suppliers' bidding in the power market.

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