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Bidding strategy of generation companies in a competitive electricity market using the shuffled frog leaping algorithm

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Abstract: In a competitive electricity market, generation companies need suitable bidding models to maximize their profit. Therefore, each supplier will bid strategically for choosing the bidding coefficients to counter the competitors' bidding strategies. In this paper, the optimal bidding strategy problem is solved using a novel algorithm based on the shuffled frog leaping algorithm (SFLA). It is a memetic metaheuristic that is designed to seek a global optimal solution by performing a heuristic search. It combines the benefits of the genetic-based memetic algorithm (MA) and the social behavior-based particle swarm optimization (PSO). This allows it to have a more precise search that avoids the premature convergence and selection of the operators. Therefore, the proposed method overcomes the short comings of the selection of operators and premature convergence of the genetic algorithm (GA) and PSO method. The most important merit of the proposed method is its high convergence speed. The proposed method is numerically verified through computer simulations on an IEEE 30-bus system consisting of 6 suppliers and a practical 75-bus Indian system consisting of 15 suppliers. The results show that the SFLA takes less computational time and produces higher profits compared to PSO and the GA.

Key words: Electricity market, bidding strategies, market clearing price, genetic algorithm, particle swarm optimization, shuffled frog leaping algorithm

1. Introduction

The global restructuring of the power industry mainly aims at abolishing the monopoly in the generation and trading sectors, thereby introducing competition at various levels wherever it is possible. However, sudden changes in the electricity markets result in a variety of new issues, such as the oligopolistic nature of the market, the supplier's strategic bidding, market power misuse, and price-demand elasticity. Theoretically, in a perfectly competitive market, suppliers should bid at, or very near to, the market clearing price (MCP) to maximize profits [1]. However, practically, the electricity markets are oligopolistic in nature, and at times the suppliers have difficulty in optimal bidding to have maximum profits by incorporating their own costs, technical constraints, and the competitors' expectations. This is known as a strategic bidding problem.

In general, there are 3 basic approaches to model the strategic bidding problem, namely a) based on the estimation of the MCP, b) based on the estimation of the rival's bidding behavior, and 3) based on game theory. David [2] developed a conceptual optimal bidding model for the first time, in which a dynamic programming (DP)-based approach has been used. Gross and Finlay adopted a Lagrangian relaxation-based approach for strategic bidding in the England-Wales pool-type electricity market [3]. Jainhui et al. [4] used an evolutionary

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game approach to analyze the bidding strategies by considering the elastic demand. Ebrahim and Galiana developed a Nash equilibrium-based bidding strategy in electricity markets [5]. David and Wen [6] proposed to develop an overall bidding strategy using 2 different bidding schemes for a day-ahead market using a genetic algorithm (GA). The same methodology has been extended for the spinning reserve market coordinated with the energy market by David and Wen [7]. Ugedo et al. developed a stochastic-optimization approach for submitting the block bids in the sequential energy and ancillary service markets, and the uncertainty in the demand and the rival's bidding behavior was estimated by stochastic residual demand curves based on decision trees [8]. To construct linear bid curves in the Nord-pool market, a stochastic programming model has been used by Fleten and Pettersen [9]. The opponents' bidding behaviors were represented as a discrete probability distribution function that was solved using the Monte Carlo method by David and Wen [10].

The deterministic approach-based optimal bidding problem was solved by Hobbs et al. [11], but it was difficult to obtain the global solution of the bilevel optimization problem because of the nonconvex objective functions and nonlinear complementary conditions used to represent the market clearing. These difficulties were avoided by representing the residual demand function with a mixed integer linear programming (MILP) model [12,13], in which the unit commitment and uncertainties were also taken into account. The generators associated with the competitors' firms have been explicitly modeled as an alternative MILP formulation based on a binary expansion of the decision variables (price and quantity bids) by Pereira et al. [14]. Azadeh et al. formed an optimal bidding problem for a day-ahead market as a multiobjective problem and solved it using a GA [15]. Jain and Srivastava [16] considered the risk constraint, for bidding single-sided and double-sided, and solved it using a GA. Ahmet et al. used PSO to determine the bid prices and quantities under the rules of a competitive power market. [17]. Kanakasabhapathy and Swarup [18] developed strategic bidding for a pumped-storage hydroelectric plant using evolutionary tristate PSO. Recently, the combination of PSO and simulated annealing (SA) was used to predict the bidding strategy of generation companies [19]. Fevrier et al. developed a new hybrid approach by combing the advantages of PSO and GAs using fuzzy logic [20].

In general, strategic bidding is an optimization problem that can be solved by various conventional and nonconventional (heuristic) methods. Depending on the bidding models, the objective function and constraints may not be differentiable; in that case, conventional methods cannot be applied. Heuristic methods such as GA, SA and evolutionary programming (EP), and particle swarm optimization (PSO) have the main limitations of their sensitivity as the choice of parameters, such as the crossover and mutation probabilities in the GA, temperature in SA, scaling factor in EP, and inertia weight and learning factors in PSO.

The shuffled frog leaping algorithm (SFLA) overcomes the shortcomings of PSO and the GA, because it is a memetic metaheuristic that is based on the evolution of the memes carried by interactive individuals and a global exchange of information among the frog population. It combines the advantages of the genetic-based memetic algorithm (MA) and social behavior-based PSO algorithm, with such characteristics as a simple concept, few parameter adjustments, prompt formation, great capability in the global search, and easy implementation.

The main contribution of this paper is a new optimization paradigm based on SFLA, which is introduced for the first time to solve the optimal bidding strategy problem. The result shows that the proposed algorithm can generate a better quality solution within a shorter computation time and stable convergence characteristics compared to PSO and the GA. The paper is organized as follows. Section 2 presents the mathematical formulation of the optimal bidding problem. Section 3 contains a brief review of the proposed SFLA method. Section 4 describes the application of the SFLA to the optimal bidding problem. Section 5 reports the case

studies solving the optimal bidding problem for the IEEE 30-bus system and practical 75-bus Indian system, and Section 6 ends with the conclusion.

2. Problem formulation

Consider a system consisting of 'm' suppliers participating in a pool-based single-buyer electricity market, in which a sealed auction with a uniform MCP is employed. Assume that each supplier is required to bid a linear supply function to the pool. The jth supplier bids with a linear supply curve, denoted by $G_j(P_j) = a_j + b_j P_j$ for $j = 1, 2\ldots m.$, where P_j is the active power output, and a_j and b_j are the nonnegative bidding coefficients of the jth supplier. After receiving bids from the suppliers, the pool determines a set of generation outputs that meets the load demand and minimizes the total purchasing cost. It is clear that the generation dispatching should satisfy Eqs. (1), (2), and (3):

$$a_j + b_j P_j = R j = 1, 2\ldots m, \tag{1}$$

$$\sum_{j=1}^{m} P_j = Q(R), \tag{2}$$

$$P_{\min,j} \leq P_j \leq P_{\max,j} j = 1, 2\ldots\ldots m, \tag{3}$$

where R is the MCP of the electricity to be determined and $Q(R)$ is the aggregate pool load forecast as follows:

$$Q(R) = Q_o - KR. \tag{4}$$

K is a nonnegative constant and is used to represent the load price elasticity. When the inequality constraint in Eq. (3) is ignored, the solutions to Eqs. (1) and (2) are:

$$R = \frac{Q_o + \sum_{j=1}^{m} \frac{a_j}{b_j}}{K + \sum_{j=1}^{m} \frac{1}{b_j}}, \tag{5}$$

$$P_j = \frac{R - a_j}{b_j} j = 1, 2\ldots\ldots m, \tag{6}$$

where $P_{min,j}$ and $P_{max,j}$ are the generation output limits of the jth supplier. If the solution to Eq. (3) exceeds the maximum limit $P_{max,j}$, P_j is set to $P_{\max,j}$. when P_j is less than $P_{min,j}$, P_j is set to 0 and the relevant supplier is removed from the problem as a noncompetitive participant for that hour. The jth supplier has a cost function denoted by $C_j(P_j) = e_j P_j + f_j P_j^2$, where e_j and f_j are the cost coefficients of the jth supplier. In a perfectly competitive market, $a_j = e_j$ and $b_j = f_j$.

The profit maximization objective of a supplier $j(j = 1, 2\ldots m)$ in a unit time for building the bidding strategy can be described as:

$$\text{Maximize: } F(a_j, b_j) = RP_j - C_j(P_j), \tag{7}$$

Subject to: Eqs. (5) and (6).

The objective is to determine the bidding coefficients a_j and b_j, so as to maximize $F(a_j, b_j)$, subject to the constraints in Eqs. (5) and (6). The jth supplier does not know the bidding coefficients of the rivals before

the auction. However, in a sealed bid auction-based electricity market, information for the next bidding period is confidential, in which the suppliers cannot solve the optimization problem using Eq. (7) directly. However, the bidding information of the previous round will be disclosed after the independent system operator decides the MCP, and everyone can make use of this information to strategically bid for the next round of transactions between the suppliers [10]. An immediate problem for each supplier is how to estimate the bidding coefficients of their rivals.

Let, from the ith supplier's point of view, the rival's jth ($j \neq i$) bidding coefficients, a_j and b_j, obey a joint normal distribution with the following probability density function (pdf):

$$pdf_i(a_j, b_j) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}},$$

$$\times \exp\left\{ -\frac{1}{2(1-\rho_j^2)} \left[\begin{array}{c} \left(\frac{a_j-\mu_j^{(a)}}{\sigma_j^{(a)}}\right)^2 - \frac{2\rho_j(a_j-\mu_j^{(a)})(b_j-\mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} \\ + \left(\frac{b_j-\mu_j^{(b)}}{\sigma_j^{(b)}}\right)^2 \end{array} \right] \right\},$$

(8)

where ρ_j is the correlation coefficient between a_j and b_j. $\mu_j^{(a)}, \mu_j^{(b)}, \sigma_j^{(a)}$, and $\sigma_j^{(b)}$ are the parameters of the joint distribution. The marginal distributions of a_j and b_j are both normal with mean values of $\mu_j^{(a)}$ and $\mu_j^{(b)}$, and standard deviations of $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$, respectively. Based on the historical bidding data, these distributions can be determined [21]. Using the pdf, the joint distribution between a_j and b_j, with the objective function in Eq. (7) and the constraints in Eqs. (5) and (6) for the optimal bidding strategy problem, becomes a stochastic optimization problem. The optimum values of b_j are searched for in the interval between $[b_j, M \times b_j]$. The optimum value of M is set to 10 by trial and error in all of the simulations, since this range is wide enough for the search space. The proposed SFLA is applied to solve the above stochastic optimization problem presented in the following section. The same problem is also implemented using a GA and PSO and are shown in Appendices A and B.

3. The proposed SFLA

The SFLA is a metaheuristic optimization method based on observing, imitating, and modeling the behavior of a group of frogs when searching for the location that has the maximum amount of available food [22]. The most distinguished benefit of the SFLA is its fast convergence speed. The SFLA combines the benefits of both the genetic-based MA and the social behavior-based PSO algorithm. In the SFLA, there is a population of possible solutions defined by a set of virtual frogs partitioned into different groups, which are described as memeplexes, each performing a local search. Within each memeplex, the individual frogs hold ideas, which can be infected by the ideas of other frogs. After a defined number of memetic evolution steps, ideas are passed between the memeplexes in a shuffling process. The local search and the shuffling process continue until the defined convergence criterion is satisfied. The flowchart of the SFLA is illustrated in Figure 1.

In the first step of this algorithm, an initial population of frogs is randomly generated within the feasible search space. The position of the ith frog is represented as $X_i = (X_{i1}, X_{i2}. \ldots. X_{iD})$, where D is the number of variables. Next, the frogs are sorted in descending order according to their fitness. Afterwards, the entire population is partitioned into m subsets, referred to as memeplexes, each containing n frogs (i.e. $P = m \times n$).
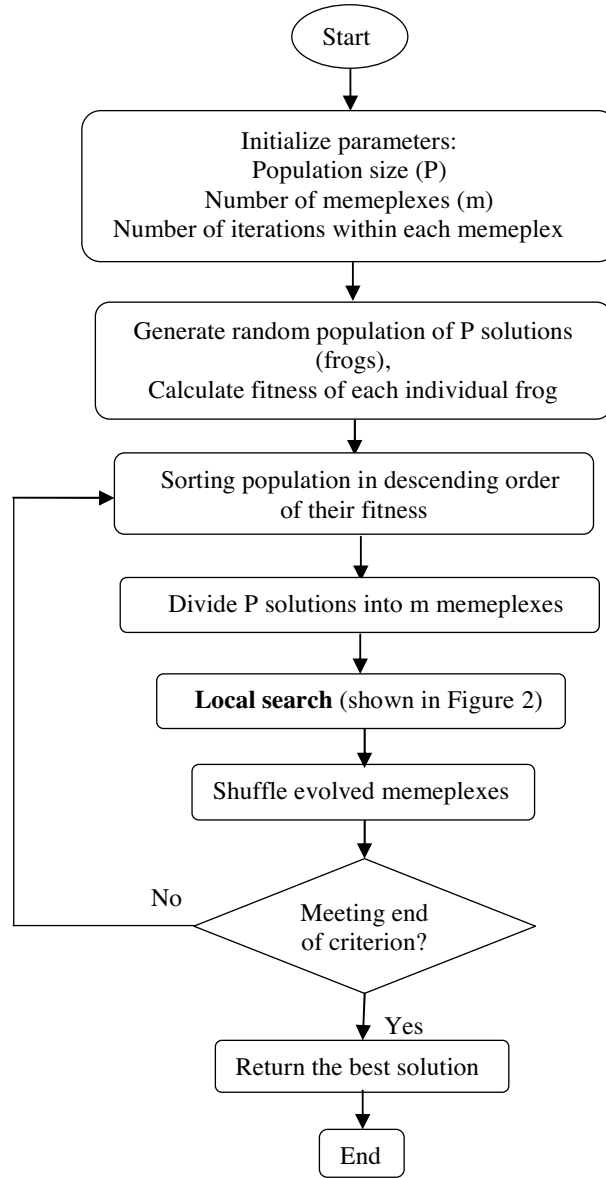
Figure 1. Flowchart for the proposed SFLA.

The strategy of the partitioning is as follows: the 1st frog goes to the 1st memeplex, the 2nd frog goes to the 2nd memeplex, the mth frog goes to the mth memeplex, the $(m+ 1)$th frog goes back to the 1st memeplex, and so forth. In each memeplex, the positions of the frogs with the best and worst fitnesses are identified as X_b and X_w, respectively. Moreover, the position of a frog with the best global fitness is identified as X_g. Next, within each memeplex, a process similar to the PSO algorithm is applied to improve only the frog with the worst fitness (not all of the frogs) in each cycle. Therefore, the position of the frog with the worst fitness leaps toward the position of the best frog, as follows:

$$Change\,in\,frog\,position = D_i = Rand \times (X_b - X_w),\qquad(9)$$

$$New\,position = X_w^{new} = X_w^{current} + D_i(D_{i\,\min} < D_i < D_{i\,\max}),\qquad(10)$$

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where $D_{i \ min}$ and $D_{i \ max}$ are the maximum and minimum step sizes allowed for a frog's position, respectively. If this process produces a better solution, it will replace the worst frog. Otherwise, the calculations in Eqs. (9) and (10) are repeated, but X_b is replaced by X_g. If there is no improvement in this case, a new solution will be randomly generated within the feasible space to replace it. The calculations will continue for a specific number of iterations [23]. Therefore, the SFLA simultaneously performs an independent local search in each memeplex using a process similar to the PSO algorithm. The flowchart of local search of the SFLA is illustrated in Figure 2.
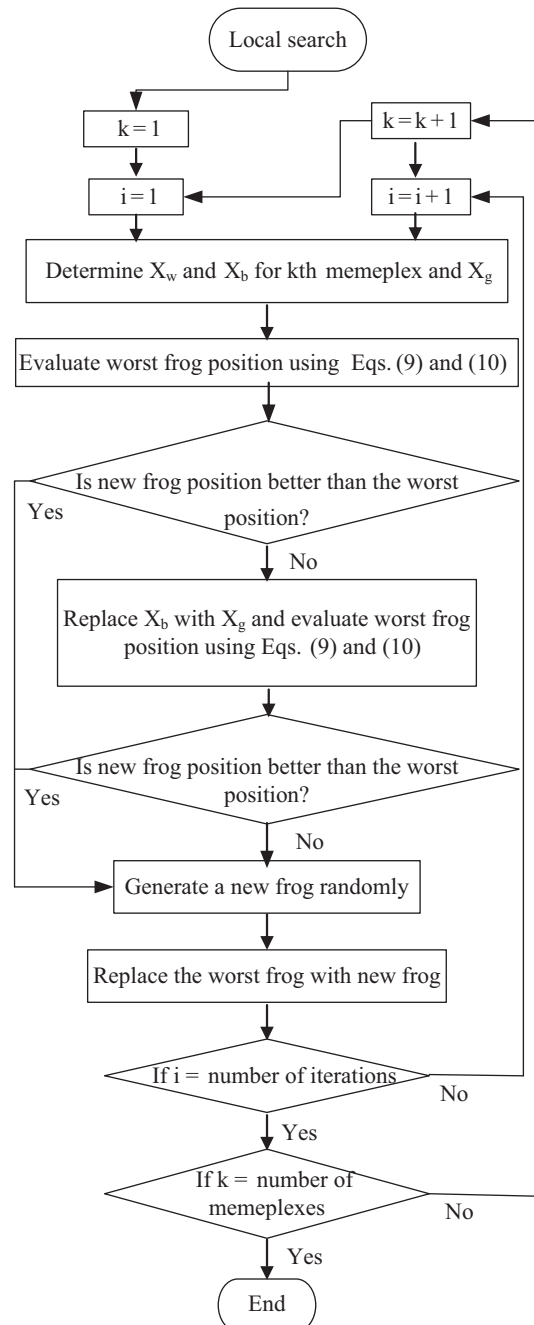

Figure 2. Flowchart of the local search.

After a predefined number of memetic evolutionary steps within each memeplex, the solutions of the evolved memeplexes $(X_1 \ldots, X_P)$ are replaced into a new population (new population $= \{X_{k}, k = 1\ldots P\}$), which is called the 'shuffling process'. The shuffling process promotes a global information exchange among the frogs. Next, the population is sorted in the order of decreasing performance values and updates the population's best frog's position; repartitioning the frog group into the memeplexes, and progresses the evolution within each memeplex until the conversion criteria is satisfied. Usually, the convergence criteria can be defined as follows [24]:

- The relative change in the fitness of the global frog within a number of consecutive shuffling iterations is less than a prespecified tolerance.

- The maximum predefined number of shuffling iterations has been obtained.

4. Application of the SFLA to the bidding problem

The problem of building an optimal bidding strategy for suppliers is described by Eq. (7) as objective functions and Eqs. (5) and (6) as constraints, and can be solved directly using the SFLA method. It is obvious that for maximizing the benefit of a supplier, the pair coefficients, (a_j, b_j) cannot be selected independently. In other words, a supplier can fix 1 of these 2 coefficients and then determine the other using an optimization procedure. In the bidding problem, the frog with highest fitness, i.e. X_g, representing the bidding parameter is optimized. In this case, Eq. (8) is used to determine the optimum values of b_j.

4.1. SFLA for obtaining the optimal bidding coefficients (b_j)

Step1. Initialization

(a) Generate a random population of b_j solutions (frogs) in the interval between (b_j and $M \times b_j$) //where b_j is the bidding parameter of the jth supplier to be optimized and M is a constant value//.

(b) Read the input data μ, σ, ρ, a, and the maximum iterations //where $\mu =$ mean, $\sigma =$ standard deviation, $\rho =$ correlation coefficient of Eq. (8), and $a =$ cost coefficient//.

Step2. For each individual b_j: calculate the fitness (b_j) using Eq. (8)

Step3. Sorting and distribution

(a) Sort (b_j) in descending order based on their fitness.

(b) Partition (b_j) into m memeplexes, each containing n frogs (i.e.$b_j = m \times n$) //where the 1st frog is distributed to the 1st memeplex, the 2nd frog is distributed to the 2nd memeplex, the m frog is distributed to the m memeplex, and the $m+$ 1 frog is distributed to the 1st memeplex, etc//.

Step4. Memeplex evolution

(a) Determine X_b , X_w, and X_g //frogs with the best and the worst fitness are identified as X_b and X_w, and the frog with the best global fitness is identified as X_g, separately//.

(b) Apply Eqs. (9) and (10) by replacing X_b with X_g and shuffle the memeplexes //to improve the worst solution//.

Step5. Shuffling

(a) Repeat the steps in Eqs. (2) to (4) for a specific number of iterations.

Step6. Terminal condition

(a) If a global solution or a fixed iteration number is reached, the algorithm stops. Print the values of (b_j) and calculate the MCP using Eq. (5).

4.2. SFLA for profit maximization

Step1. Initialization

(a) Generate a random population of the profit F_j solutions (frogs) in the search space //where F$_j$ is the profit of the jth supplier//.

(b) Read the input data of the generators (i.e. cost coefficients, P_{min}, P_{max}), demand (Q_o) and the maximum iterations.

Step2. Calculate the generator outputs of each supplier using Eq. (6)

(a) If the generation violates the lower limit, set it as a lower limit.

If the generation violates the upper limit, set it as an upper limit.

(b) Add all of the generations.

(c) Error = generation – demand.

Step3. For each individual supplier, calculate the fitness (i.e. error)

Step4. Sorting and distribution

(a) Sort the profits (F$_j$) in descending order based on their fitness.

(b) Partition (F_j) into m memeplexes, each containing n frogs (i.e. $F_j = m \times n$) //where the 1st frog is distributed to the 1st memeplex, the 2nd frog is distributed to the 2nd memeplex, the m frog is distributed to the m memeplex, and the $m+$ 1 frog is distributed to the 1st memeplex, etc//.

Step5. Memeplex evolution

(a) Determine X_b, X_w, and X_g //frogs with the best and the worst fitness are identified as X_b and X_w, and the frog with the best global fitness is identified as X_g, separately//.

(b) Apply Eqs. (9) and (10) by replacing X_b with X_g and shuffle the memeplexes //to improve the worst solution//.

Step6. Shuffling

(a) Repeat the steps in Eqs. (3) to (5) until the stop criteria are reached, i.e. error ≤ 0.0001

Step7. Terminal condition

(a) If a global solution or a fixed iteration number is reached, the algorithm stops. Print the values of the profit (F_j) of each generator.

(b) Print the central processing unit (CPU) time and plot the number of iterations versus percentage error, where

$$\%Error = \frac{Generation - Demand}{Generation} \times 100.$$

The pseudo-code for the algorithm is given in Table 1.

Table 1. Pseudo-code for the proposed SFLA.

Begin;

Generate a random population of P solutions (frogs);

For each individual $i \in P$: calculate fitness (i);

Sort the population P in descending order of their fitness;

Divide P into m memeplexes;

For each memeplex;

Determine the best and worst frogs;

Improve the worst frog position using Eqs. (9) and (10);

Repeat for a specific number of iterations;

End;

Combine the evolved memeplexes;

Sort the population P in descending order of their fitness;

Check if the termination = true;

End;

5. Simulation and discussions

In order to evaluate the performance of the proposed method for solving the optimal bidding problem, the IEEE 30-bus system and a practical 75-bus Indian system are considered. In this work, the parameters used for the SFLA, PSO, and GA are given in Table 2. The simulations are carried out on a 2.66-GHz PIV processor with 3-GB RAM and MATLAB version 7.8 is used.

Table 2. Parameter values used for the IEEE 30-bus system and the 75-bus Indian system.

SFLA	PSO	GA
P = 200; m = 20;	No. of particles = 200;	Population size = 200;
Max. iterations 1000.	Max. iterations = 1000;	Generations = 1000;
	$c1$ = $c2$ = 2.0; w = 0.9 to 0.4	L = $10, P_e$ = 0.15;
		P_c =0.85; P_m = 0.005

P: population of frogs; m: No. of memeplexes for the SFLA; $c1$, $c2$: learning factors; w: inertia weight for PSO; Pe: elitism probability; Pc: crossover probability; Pm: mutation probability; and l: string length for the GA.

5.1. IEEE 30-bus system [10]

The IEEE 30-bus system consists of 6 suppliers, who supply electricity to the aggregate load. The generator data was taken from [10]. Q_o is 500 with an inelastic load (K = 0), considered for the aggregated load. The bidding strategies are shown in Table 3. The optimal bid prices and profits are shown in Table 4. From Tables 3 and 4 it is observed that the proposed SFLA gives the maximum power outputs and higher profits. Therefore, the bidding parameters obtained by the SFLA are optimum compared to those from PSO, the GA, and the Monte Carlo [10] method. Figure 3 shows the variation in the profit of each supplier for the different methods. The convergence characteristics of the proposed SFLA method, PSO, and the GA are shown in Figure 4 and it is observed that the proposed SFLA method converged in 20 iterations because of the more precise search, whereas PSO and the GA converged in 27 and 30 iterations, respectively. Therefore, the proposed method converges fast compared to PSO and the GA.

Table 3. Optimal bidding strategies for the IEEE 30-bus system.

	SFLA	PSO	GA	Monte Carlo [10]
Generator	b_j	b_j	b_j	b_j
1	0.021004	0.001092	0.001045	0.15800
2	0.090472	0.050953	0.048786	0.04745
3	0.263450	0.181976	0.174234	0.13099
4	0.054320	0.024283	0.023250	0.02458
5	0.108594	0.072791	0.069694	0.05614
6	0.108594	0.072791	0.069694	0.56140

Table 4. MCP ($/MWh) and profit ($) of the generators for the IEEE 30-bus system.

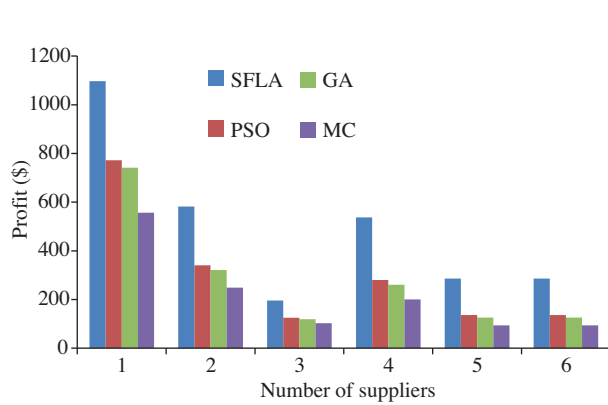|	SFLA		PSO		GA		Monte Carlo [10]	
Generator	P (MW)	Profit ($)	P (MW)	Profit ($)	P (MW)	Profit ($)	P (MW)	Profit ($)
1	160.00	1097.16	160.00	772.41	160.00	741.45	160.00	557
2	96.76	581.93	100.83	340.10	101.34	321.32	91.3	249
3	29.73	196.19	32.35	125.06	32.68	119.33	38.8	103
4	100.00	537.32	100.00	280.36	100.00	261.01	100.00	200
5	56.75	285.94	53.40	136.32	53.00	125.56	54.90	94
6	56.75	285.94	53.40	136.32	53.00	125.56	54.90	94
MCP	9.45		6.88		6.69		6.08	
Total profit	2984.50		1790.57		1694.23		1297	

Figure 3. Expected profit of the suppliers and consumers for the IEEE 30-bus system.
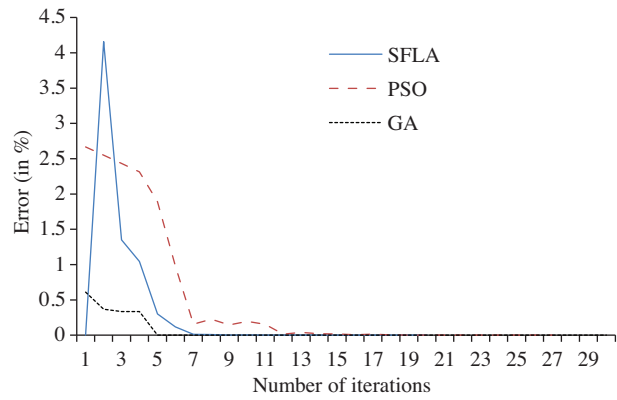

Figure 4. Convergence characteristics of the SFLA, PSO, and GA for the IEEE 30-bus system.

5.2. Practical 75-bus Indian system [25]

The 75-bus Indian system consists of 15 suppliers, who supply electricity to the aggregate load. Q_o is 1000 and K is 10, considered for the aggregated load. The bidding coefficients, generator output, MCP, and profit of the suppliers are calculated using the SFLA, shown in Tables 5 and 6. Figure 5 shows the variation of the profit of the suppliers. Figure 6 shows the convergence characteristics of the different methods and it is observed that the proposed SFLA converged in 24 iterations, whereas PSO and the GA converged in 47 and 58 iterations, respectively. Therefore, even if the size of the system increases, the proposed method still shows better convergence characteristics, because the SFLA combines the benefits of both the genetic-based MA and the social behavior-based PSO algorithm.

Table 5. Optimal bidding strategies for the 75-bus Indian system.

	SFLA	PSO	GA
Generator	b_j	b_j	b_j
1	0.002924	0.002200	0.002944
2	0.004509	0.003232	0.004774
3	0.002369	0.006976	0.003918
4	0.006296	0.006762	0.002844
5	0.334051	0.134368	0.196915
6	0.011553	0.011002	0.005410
7	0.019105	0.006162	0.012133
8	0.004908	0.009800	0.004973
9	0.010374	0.008323	0.004177
10	0.006258	0.003392	0.003222
11	0.005537	0.002952	0.003222
12	0.007409	0.005573	0.003063
13	0.004727	0.002035	0.002964
14	0.002403	0.005630	0.002665
15	0.006110	0.002529	0.003640

The superiority of the SFLA approach is demonstrated through a comparison of the simulation results with PSO and the GA. Due to the randomness of the evolutionary algorithms, their performances cannot be

judged by the results of a single run. Many trails with different initializations should be made to reach a valid conclusion about the performance of the algorithms. An algorithm is robust if it can guarantee an acceptable performance level under different conditions. Since the SFLA, PSO, and GA are random in nature, the bidding data were executed 20 times for all of the approaches. The best, worst, and average values of the total profit and the percentage deviation (PD) for the given data are tabulated in Tables 7 and 8, respectively. The PD is computed as follows:

$$PD = \frac{(Best - Worst)}{Best} \times 100\%.$$

Table 6. MCP (Rs/MWh) and profit (Rs) of the generators for the 75-bus Indian system.

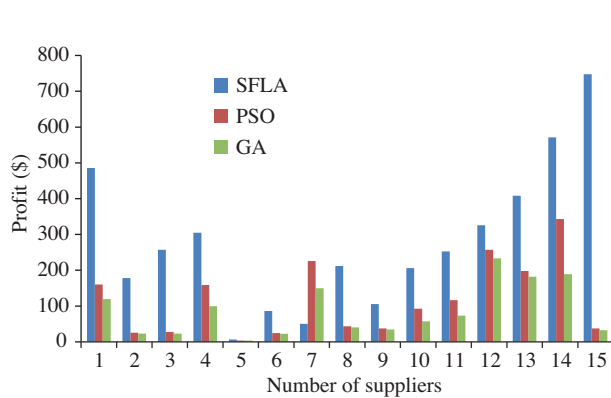| Generator	SFLA		PSO		GA	
	P (MW)	Profit (Rs)	P (MW)	Profit (Rs)	P (MW)	Profit (Rs)
1	333.48	485.76	471.3	160.02	171.7	119.7
2	164.14	178.30	175.4	25.6	56.6	22.9
3	280.00	256.98	74.1	27.5	62.6	23.0
4	165.20	304.62	172.6	158.8	100	99.8
5	3.44	6.74	10.3	3.7	3.4	3.5
6	64.92	85.93	54.2	24.3	52.7	22.5
7	39.52	50.16	160	225.7	80	149.8
8	170.15	211.80	77.2	43.5	73.5	40.2
9	75.19	105.44	77.7	37.6	74.3	34.5
10	137.44	205.82	180	92.7	90	57.1
11	163.46	252.61	209	116.7	104.5	73.3
12	156.58	325.54	252.5	257.1	225.4	233.1
13	226.38	408.14	603.1	198.1	202.6	182.2
14	250.00	571.30	250	343.0	125	189.2
15	270.00	747.60	232.1	37.6	77.0	32.39
MCP	8.60		7.68		7.56	
Total profit	4196.80		1752.6		1283.89	

Figure 5. Expected profit of the suppliers for the practical 75-bus Indian system.
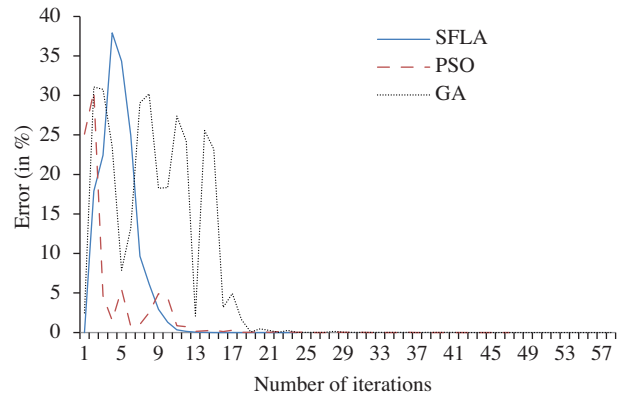

Figure 6. Convergence characteristics of the SFLA, PSO, and GA for the 75-bus Indian system.

Tables 7 and 8 show that the PD is minimum for the proposed SFLA method compared to PSO and the GA, for the IEEE 30-bus system as well as the 75-bus Indian system, and it is clearly observed that the optimal

bidding strategies obtained by the SFLA produced higher profits compared to PSO and GA. In addition, the SFLA shows good consistency by keeping a small variation between the best and worst solution. In other words, the simulation results show that the SFLA algorithm converges to a global solution, has a shorter CPU time, and a small percentage deviation, because it combines the advantages of both the MA and PSO. As a result, the frogs tend to move towards the best position, which avoids a premature convergence and permits a faster convergence.

Table 7. Performance comparison of the different approaches for the IEEE 30-bus system.

		SFLA	PSO	GA
Total profit ($)	Best ($)	2984.50	1790.57	1694.23
	Worst ($)	2792.34	1574.85	1464.27
	Ave. ($)	2888.42	1682.71	1579.25
	PD (%)	0.064	0.120	0.135
Average CPU time (s)		0.251	6.24	12.28

Table 8. Performance comparison of the different approaches for the 75-bus Indian system.

		SFLA	PSO	GA
Total profit (Rs)	Best (Rs)	4196.80	1752.6	1283.89
	Worst (Rs)	4092.16	1627.34	1092.06
	Ave. (Rs)	4144.48	1689.97	1187.97
	PD (%)	0.024	0.071	0.149
Average CPU time (s)		0.4235	10.725	18.462

6. Conclusion

In this paper, the SFLA is proposed for the first time to solve the bidding strategies for generation companies in a competitive electricity market. It is a memetic metaheuristic that is based on the evolution of memes carried by interactive individuals and a global exchange of information among the frog population. It combines the advantages of the genetic-based MA and social behavior-based PSO algorithm, with such characteristics as a simple concept, fewer parameter adjustments, prompt formation, great capability in a global search, and easy implementation. The effectiveness of the proposed SFLA has been tested on an IEEE 30-bus system and a practical 75-bus Indian system. The results were compared with those from PSO and the GA. The numerical results reveal the superiority of the proposed SFLA compared to PSO and the GA with respect to the total profit and the convergence of CPU time. Therefore, the proposed algorithm gives more profit and converges very rapidly so that it can be used for real-time applications. In future, the same bidding problem will also be extended for analyzing the pricing mechanism for microgrid energy in the competitive electricity market, where the microgrid central controller is made to participate in the bidding process to settle the MCP.

Appendix A

(i). GA for obtaining the optimal bidding coefficients (b_j)

Step1. Initialization

(a) The initial strings are randomly generated in the interval between (b_j and $M \times b_j$) //where b_j is the bidding parameter of the jth supplier to be optimized and M is a constant value//.

(b) Read the input data μ, σ, ρ, and a, and the maximum iterations. //where μ = mean, σ = standard deviation, ρ = correlation coefficient of Eq. (8), and a = cost coefficient//.

Step2. The generated string is converted into the feasible range from the following:

Actual _ Value (i) = b _ min + ((b _ max − b _ min) × b _ m(i)) / (2(l − 1)), where l = the string length,

b_min = minimum value of b_j,

b_max = maximum value of b_j,

b_m (i) = the decimal value of jth supplier in the string.

Step3. The fitness of each chromosome is calculated according to the probability function mentioned in Eq. (8). The values obtained from the probability function are sorted and those that have the highest value are selected for the next generation.

Step4. The selected chromosomes are considered for the crossover operation.

Step5. After the crossover operation, the new offspring are considered for the mutation operation.

Step6. The fitness of the new offspring is calculated and they are sorted in ascending order.

The highest bidding parameter means better fitness. Hence, the highest bidding parameter values are selected for the next generation.

Step7. The process is repeated up to the maximum number of iterations.

(ii). GA for profit maximization

Step1. Initialization

(a) The initial strings of the profit F_j are randomly generated //where F$_j$ is the profit of the jth supplier.

(b) Read the input data of the generators (i.e. cost coefficients, P_{min}, P_{max}), demand (Q_o), and the maximum iterations.

Step2. The generated string is converted into the feasible range from the following:

Actual _ Value (i) = P _ min + ((P _ max − P _ min) × p _ m(i)) /(2(l − 1)), where l = the string length,

P_min = minimum value of the generating unit,

P_max = maximum value of the generating unit,

p_m (i) = the decimal value of ith generating unit in the string.

Step3. The equality constraint is checked according to Eq. (2)

Step4. The fitness of each chromosome is calculated according to the profit function mentioned in Eq. (7). The values obtained from profit function are sorted and those that have the highest value are selected for the next generation.

Step5. The selected chromosomes are considered for the crossover operation.

Step6. After the crossover operation, the new offspring are considered for the mutation operation.

Step7. The fitness of the new offspring is calculated and they are sorted in ascending order.

The highest profit function means a better fitness. Hence, the highest profit function values are selected for the next generation.

Step8. The process is repeated up to the maximum number of iterations.

Appendix B

(i). PSO for obtaining the optimal bidding coefficients (b_j)

Step1. Initialization of the particles

(a) Generate a random population of b_j solutions //where b_j is the bidding parameter of the jth supplier to be optimized//.

(b) Read the input data μ, σ, ρ, and a, and the maximum iterations //where μ = mean, σ = standard deviation, ρ = correlation coefficient of Eq. (8), and a = cost coefficient//.

Step2. The evaluation function of each individual b_j is calculated in the population using Eq. (8)

Step3. Each of the P_{best} values are compared with the other P_{best} values in the population. The best evaluation value among the P_{best} is denoted as G_{best}

Step4. The member velocity V of each individual bi is modified according to the velocity update:

$$V_r^{k+1} = w^k V_r^k + a_1 rand_1 \times (P_{best}^k - X_r^k) + a_2 rand_2 \times (G_{best}^k - X_r^k) \quad .$$

Step5. The position of each individual b_j is modified according to the position update equation:

$$X_r^{k+1} = X_r^k + V_r^{k+1}.$$

Step6. Repeat Steps 2–5 until the iterations reach their maximum limit. Return the best fitness (optimal bid value b_j) computed at the final iteration as a global fitness.

(ii). PSO for profit maximization

Step1. Initialization of the particles

(a) Generate a random population of the profit F_j solutions //where F_j is the profit of

the jth supplier//.

(b) Read the input data of the generators (i.e. cost coefficients, Pmin, Pmax), demand (Qo), and the maximum number of iterations.

Step2. Calculate the generator output of each supplier using Eq. (6)

(a) If the generation violates the lower limit, set it as a lower limit.

If the generation violates the upper limit, set it as an upper limit.

(b) Add all of the generations.

(c) Error = total system generation – total system demand.

Step3. Fitness evaluation using Eq. (7)

Step4. Each of the P_{best} values are compared with the other P_{best} values in the population. The best evaluation value among the P_{best} is denoted as G_{best}.

Step5. The member velocity V of each individual F_j is modified according to the velocity update:

$$V_r^{k+1} = w^k V_r^k + a_1 rand_1 \times (P_{best}^k - X_r^k) + a_2 rand_2 \times (G_{best}^k - X_r^k)$$.

Step6. The position of each individual F_j is modified according to the position update:

$$X_r^{k+1} = X_r^k + V_r^{k+1}.$$

Step7. Repeat Steps 3–6 until the iterations reach their maximum limit. Return the best fitness (maximum profit) computed at the final iteration as a global fitness.

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