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# Generation bidding strategy in a pool based electricity market using Shuffled Frog Leaping Algorithm

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ABSTRACT

In an electricity market generation companies need suitable bidding models to maximize their profits. Therefore, each supplier will bid strategically for choosing the bidding coefficients to counter the competitors bidding strategy. In this paper optimal bidding strategy problem is solved using a novel algorithm based on Shuffled Frog Leaping Algorithm (SFLA). It is memetic meta-heuristic 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). Due to this it has better precise search which avoids premature convergence and selection of operators. Therefore, the proposed method overcomes the short comings of selection of operators and premature convergence of Genetic Algorithm (GA) and PSO method. Important merit of the proposed SFALA is that faster convergence. The proposed method is numerically verified through computer simulations on IEEE 30-bus system consist of 6 suppliers and practical 75-bus Indian system consist of 15 suppliers. The result shows that SFLA takes less computational time and producing higher profits compared to Fuzzy Adaptive PSO (FAPSO), PSO and GA.



## 1. Introduction

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. But the sudden changes in the electricity markets have a variety of new issues such as oligopolistic nature of the market, supplier's strategic bidding, market power misuse, price-demand elasticity and so on. 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 nature, and power suppliers may seek to increase their profit by bidding a price higher than MCP. Knowing their own costs, technical constraints and their expectation of rival and market behavior, suppliers face the problem of constructing the best optimal bid. This is known as a strategic bidding problem.

In general, there are three basic approaches to model the strategic bidding problem viz. (i) based on the estimation of Market Clearing Price, (ii) estimation of rival's bidding behavior and (iii) 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 Finaly adopted a Lagrangian relaxation-based approach for strategic bidding in England-Wales pool type electricity market [3]. Jainhui et al. [4] used evolutionary game approach to analyzing bidding strategies by considering elastic demand. Ebrahim and Galiana developed Nash equilibrium based bidding strategy in electricity markets [5]. David and Wen [6] proposed to develop an overall bidding strategy using two different bidding schemes for a day-ahead market using Genetic Algorithm (GA). The same methodology has been extended for spinning reserve market coordinated with energy market by David and Wen [7]. Ugedo et al. developed a stochastic-optimization approach for submitting the block bids in sequential energy and ancillary services markets and uncertainty in demand and rival's bidding behavior is estimated by stochastic residual demand curves based on decision trees [8]. To construct linear bid curves in the Nord-pool market stochastic programming model has been used by Fleten et al. [9]. The opponents' bidding behaviors are represented as a discrete probability distribution function solved using Monte Carlo method by David and Wen [10].

The deterministic approach based optimal bidding problem was solved by Hobbs et al. [11], but it is difficult to obtain the global solution of bi-level optimization problem because of non-convex objective functions and non-linear complementary conditions to represent market clearing. These difficulties are avoided by

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representing the residual demand function by Mixed Integer Linear Programming (MILP) model [12,13], in which unit commitment and uncertainties are also taken into account. The generators associated to 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 optimal bidding problem for day-ahead market as multi objective problem and solved using GA [15]. Jain and Srivastava [16] considered risk constraint, for bidding single sided and double sided and solved using GA. Ahmet et al. used PSO to determine bid prices and quantities under the rules of a competitive power market [17]. Kanakasabhapathy and Swarup [18] developed strategic bidding for pumped-storage hydroelectric plant using evolutionary tristate PSO. Bajpai et al. developed blocked bid model bidding strategy in a uniform price spot market using Fuzzy Adaptive Particle Swarm Optimization (FAPSO) [19]. Venkaiah et al. used Fuzzy Adaptive Bacterial Foraging Algorithm (FABFA) for optimal rescheduling of active power of generators [20]. Recently the combination of PSO and Simulated Annealing (SA) is used to predict the bidding strategy of generation companies [21]. Fevrier et al. developed a new hybrid approach by combing the advantages of PSO and GA using fuzzy logic [22].

In general, strategic bidding is an optimization problem that can be solved by various conventional and non-conventional (heuristic) methods. Depending on the bidding models, objective function and constraints may not be differentiable, in that case conventional methods cannot be applied. Whereas, heuristic methods such as GA, Simulated Annealing (SA) and Evolutionary Programming (EP), Particle Swarm Optimization (PSO), etc., have main limitations of their sensitivity to the choice of parameters, such as the crossover and mutation probabilities in GA, temperature in SA, scaling factor in EP and inertia weight, learning factors in PSO and framing of rules in fuzzy adaptive Particle Swarm Optimization (FAPSO).

Shuffled Frog Leaping Algorithm (SFLA) overcomes the shortcomings of FAPSO, PSO and GA, because it is a memetic meta-heuristic that is based on 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 Memetic Algorithm (MA) and social behavior-based PSO algorithm with such characteristics as simple concept, few parameter adjustment, prompt formation, great capability in global search and easy implementation.

The main contribution of this paper is, a new optimization paradigm based on Shuffled Frog Leaping Algorithm (SFLA) is introduced first time to solve optimal bidding strategy problem. The result shows that the proposed algorithm can generate better quality solution within shorter computation time and stable convergence characteristics compared to FAPSO, PSO and GA. The paper is organized as follows. Section 2 presents the mathematical formulation of optimal bidding problem. Section 3 contains a brief over view of the proposed SFLA method. Section 4 describes the application of SFLA for solving the optimal bidding problem. Section 5 reports the case studies solving optimal bidding problem for IEEE 30-bus system and practical 75-bus Indian system and Section 6 summed up the final outcome of the paper as Conclusion.

## 2. Problem formulation

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

$$a_j + b_jP_j = R \quad j = 1, 2, \ldots, m \tag{1}$$

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

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

where $R$ is the Market Clearing Price (MCP) of electricity to be determined, $Q(R)$ is the aggregate pool load forecast as follows

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

where $Q_o$ is a constant number and $K$ is a non-negative constant used to represent the load price elasticity. When the inequality constraint Eq. (3) is ignored, the solution to Eqs. (1) and (2) are,

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

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

$P_{\min,j}$ and $P_{\max,j}$ are the generation output limits of the $j$th supplier. If the solution of the 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 zero and relevant supplier is removed from the problem as a non-competitive participant for that hour. The $j$th supplier has the cost function denoted by $C_j(P_j) = e_jP_j + f_jP_j^2$, where $e_j$ and $f_j$ are the cost coefficients of the $j$th supplier. In a perfectly competitive market, $a_j = e_j$ and $b_j = f_j$.

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

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

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

The objective is to determine bidding coefficients $a_j$ and $b_j$ so as to maximize $F(a_j, b_j)$ subject to the constraints Eqs. (5) and (6). Since the $j$th supplier does not know the bidding coefficients of rivals before the auction. But in sealed bid auction based electricity market, information for the next bidding period is confidential in which suppliers cannot solve optimization problem using Eq. (7) directly. However, bidding information of previous round will be disclosed after Independent System Operator (ISO) decide MCP and everyone can make use of this information to strategically bid for the next round of transaction between suppliers [10]. An immediate problem of each supplier is how to estimate the bidding coefficients of rivals.

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

$$pdf_i(a_j, b_j) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}} \times \exp\left\{-\frac{1}{2(1-\rho_j^2)}\left[\left(\frac{a_j-\mu_j^{(a)}}{\sigma_j^{(a)}}\right)^2 - \frac{2\rho_j(a_j-\mu_j^{(a)})(b_j-\mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} + \left(\frac{b_j-\mu_j^{(b)}}{\sigma_j^{(b)}}\right)^2\right]\right\} \tag{8}$$

where $\rho_j$ 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 parameter of the joint distribution. The marginal distributions of $a_j$ and $b_j$ are both normal with mean values $\mu_j^{(a)}$ and $\mu_j^{(b)}$, and standard deviations $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$ respectively.

Based on historical bidding data these distributions can be determined [10]. Using *pdf*, the joint distribution between $a_j$ and $b_j$ with the objective function Eq. (7) and constraints Eqs. (5) and (6) the optimal bidding strategy problem becomes a stochastic optimization problem. The optimum values of $b_j$ are searched from interval between $[b_j, M \times b_j]$. The optimum value of $M$ is set to 10 by hit and trial in all the simulations since this range is wide enough for the search space. The proposed Shuffled Frog Leaping Algorithm (SFLA) is applied to solve the above stochastic optimization problem presented in the following section.

## 3. The proposed Shuffled Frog Leaping Algorithm (SFLA)

The SFLA is a meta-heuristic optimization method which is 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 [23]. The most distinguished benefit of SFLA is its fast convergence speed. The SFLA combines the benefits of the both the Genetic-based Memetic Algorithm (MA) and the social behavior-based PSO algorithm. In 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 memeplexes in a shuffling process. The local search and the shuffling process continue until the defined convergence criterion is satisfied. The flowchart of SFLA is illustrated in Fig. 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 $i$th frog is represented as $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$, where $D$ is the number of variables. Then, 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., $P = m \times n$). The strategy of the partitioning is as follows: the first frog goes to the first memeplex, the second frog goes to the second memeplex, the $m$th frog goes to the $m$th memeplex, the $(m+1)$th frog goes back to the first memeplex, and so forth. In each memeplex, the positions of frogs with the best and worst fatnesses' are identified as $X_b$ and $X_w$, respectively. Also the position of a frog with the global best fitness is identified as $X_g$. Then, within each memeplex, a process similar to the PSO algorithm is applied to improve only the frog with the worst fitness (not all frogs) in each cycle. Therefore, the position of the frog with the worst fitness leaps toward the position of the best frog, as follows:

$$\text{Change in frog position} = D_i = Rand \times (X_b - X_w) \tag{9}$$

$$\text{New position} = X_w^{new} = X_w^{current} + D_i (D_{imin} < D_i < D_{imax}) \tag{10}$$

where $D_{imin}$ and $D_{imax}$ 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 [24]. Therefore, SFLA simultaneously performs an independent local search in each memeplex using a process similar to the PSO algorithm. The flowchart of local search of SFLA is illustrated in Fig. 2.

After a predefined number of memetic evolutionary steps within each memeplex, the solutions of evolved memeplexes $(X_1, \ldots, X_P)$ are replaced into new population (new population = $\{X_k, k = 1, \ldots, P\}$); this is called the 'shuffling process'. The shuffling process promotes a global information exchange among the frogs. Then, the population is sorted in order of decreasing performance value and updates the population best frog's position, repartition

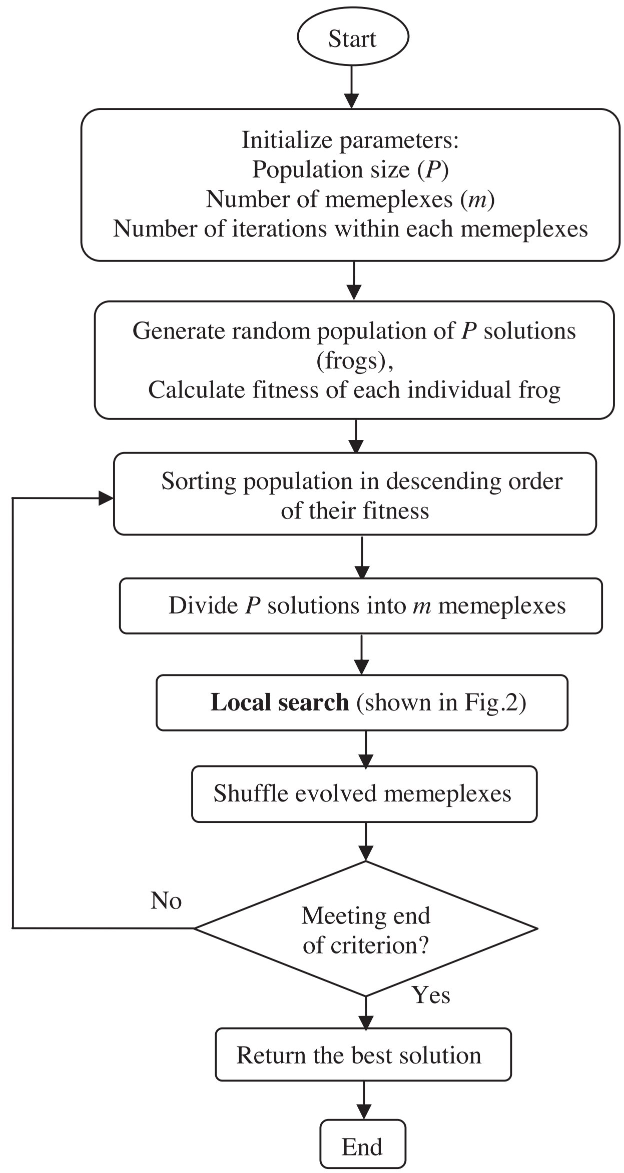


**Fig. 1.** Flowchart for the proposed SFLA.

the frog group into memeplexes, and progress the evolution within each memeplex until the convergence criteria is satisfied. Usually, the convergence criteria can be defined as follows [25]:

- The relative change in the fitness of the global frog within a number of consecutive shuffling iterations is less than a pre-specified tolerance.
- The maximum predefined number of shuffling iteration has been obtained.

## 4. Application of SFLA on 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 can be solved directly using 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 one of these two coefficients and then determine the other by using an optimization procedure. In the

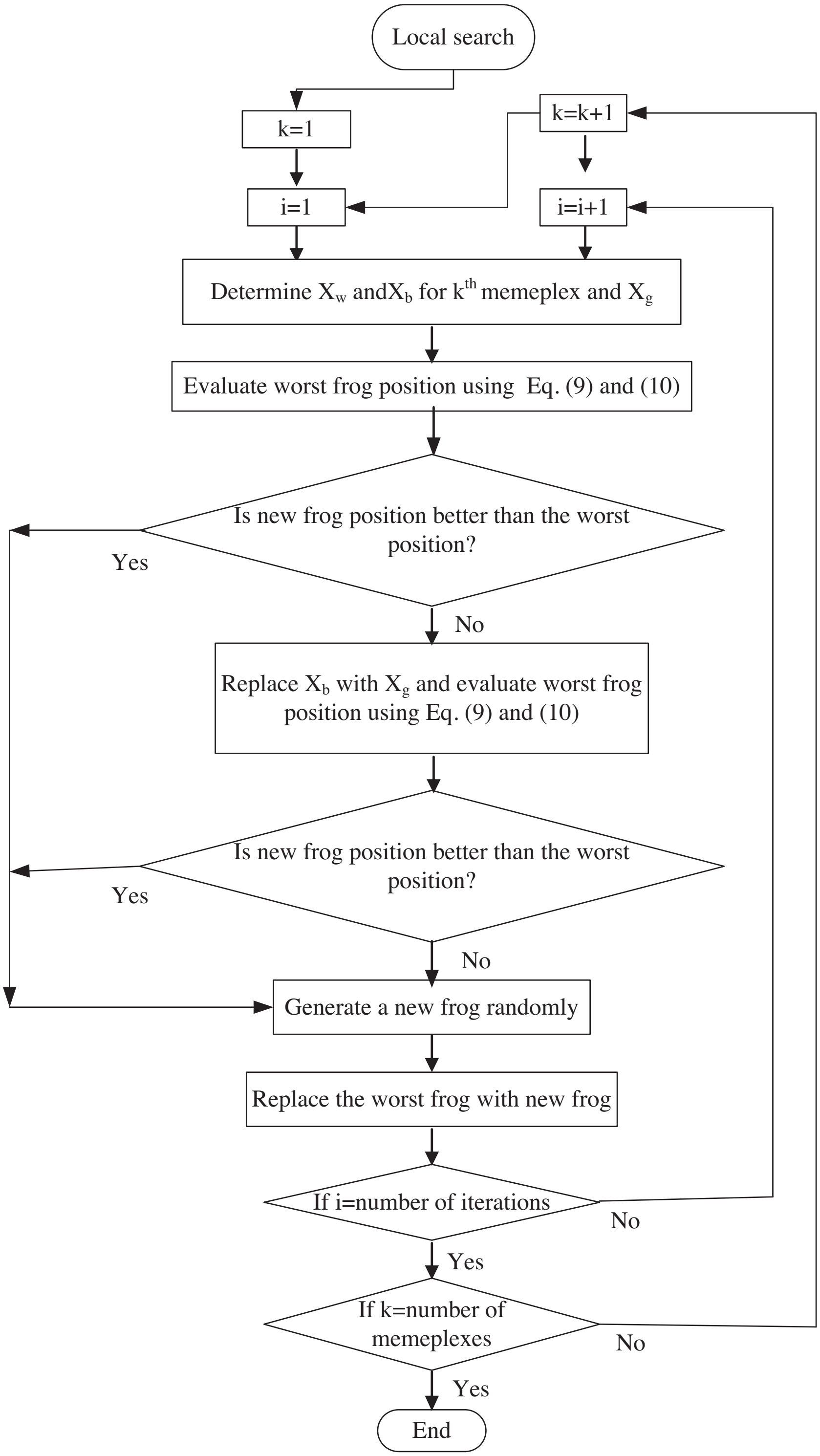


**Fig. 2.** Flowchart of local search.

bidding problem the frog with highest fitness i.e. $X_g$ represents bidding parameter is optimized. In this case Eq. (8) is used to determine the optimum values of $b_j$.

### 4.1. *SFLA for obtaining optimal bidding coefficients ($b_j$)*

Step 1. Initialization

(a) Generate 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 *j*th supplier to be optimized and *M* is a constant value//.
(b) Read input data $\mu$, $\sigma$, $\rho$, $a$ and maximum iterations. //where $\mu$ = mean, $\sigma$ = standard deviation, $\rho$ = correlation coefficient of Eq. (8), $a$ = cost coefficient//

Step 2. For each individual $b_j$: calculate fitness ($b_j$) using Eq. (8)
Step 3. Sorting and distribution

(a) Sort ($b_j$) in descending order based on their fitness.
(b) Partition ($b_j$) into $m$ memeplexes, each congaing $n$ frogs (i.e. $b_j = m \times n$) //where the first frog is distributed to the first memeplex, the second frog to the second, the $m$ frog to the $m$ memeplex, and the $m+1$ frog to the first memeplex, etc.//
Step 4. 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 global best fitness is identified as $X_g$ separately//
(b) Apply Eqs. (9) and (10) with replacing $X_b$ by $X_g$ and Shuffle the memeplexes. //To improve the worst solution//
Step 5. Shuffling
(a) Repeat steps (2)–(4) for specific number of iterations.
Step 6. 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 MCP using Eq. (5).

### 4.2. SFLA for profit maximization

Step 1. Initialization
(a) Generate random population of profit $F_j$ solutions (frogs) in the search space //where $F_j$ is the profit of the $j$th supplier.
(b) Read input data of Generators (i.e. cost coefficients, $P_{\min}$, $P_{\max}$), demand ($Q_o$) and maximum iterations.
Step 2. Calculate generator outputs of each supplier using Eq. (6)
(a) If generation violates lower limit set as a lower limit
(b) If generation violates upper limit set as an upper limit
(c) Add all generations
(d) Error = generation − demand
Step 3. For each individual supplier calculate fitness (i.e. error)
Step 4. Sorting and distribution
(a) Sort profit ($F_j$) in descending order based on their fitness
(b) Partition ($F_j$) into $m$ memeplexes, each congaing $n$ frogs (i.e. $F_j = m \times n$) //where the first frog is distributed to the first memeplex, the second frog to the second, the $m$ frog to the $m$ memeplex, and the $m+1$ frog to the first memeplex, etc.//
Step 5. 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 global best fitness is identified as $X_g$ separately//
(b) Apply Eqs. (9) and (10) with replacing $X_b$ by $X_g$ and Shuffle the memeplexes. //To improve the worst solution//
Step 6. Shuffling
(a) Repeat steps (3)–(5) until the stop criteria are reached i.e. error $\leq 0.0001$
Step 7. Terminal condition
(a) If a global solution or a fixed iteration number is reached, the algorithm stops. Print the values of profit ($F_j$) of each generator.
(b) Print c.p.u. time, plot number of iterations versus percentage error

where %Error = ((Generation − Demand)/Generation) × 100

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

**Table 1**
Pseudo-code for the proposed SFLA.

```
Begin;
Generate random population of P solutions (frogs);
For each individual i ∈ 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 termination = true;
End;
```

## 5. Simulation and discussions

In order to evaluate the performance of the proposed method for solving optimal bidding problem, IEEE 30-bus system and practical 75-bus Indian system are considered. In this work, the parameters used for SFLA, PSO and GA are given in Table 2. Inertia weight $w$ is adjusted using fuzzy rules in the case of Fuzzy Adaptive Particle Swarm Optimization (FAPSO) [19]. Simulations are carried on 2.66 GHz, PIV Processor, 3GB RAM and MATLAB 7.8 version is used.

**Table 2**
Parameter values used for different approaches for IEEE 30-bus system and 75-bus Indian system.

| SFLA | FAPSO | PSO | GA |
|---|---|---|---|
| $P = 200$; $m = 20$; Max. iterations 1000 | Inertia weight '$w$' is adjusted using fuzzy rules | No. of particles = 200; Max. iterations = 1000; $c_1 = c_2 = 2.0$; $w = 0.9$–$0.4$ | Population size = 200; generations = 1000; $P_e = 0.15$; $P_c = 0.85$; $P_m = 0.005$ |

$P$, population of frogs; $m$, no. of memeplexes for SFLA; $c_1$, $c_2$, learning factors; $w$, inertia weight for PSO; $P_e$, elitism probability, $P_c$, crossover probability $P_m$, mutation probability for GA.

### 5.1. IEEE 30-bus system [10]

The IEEE 30-bus system consists of six suppliers, who supply electricity to aggregate load. The Generator data is shown in Table 3. $Q_o$ is 500 with inelastic load ($K = 0$), considered for aggregated demand. Bidding strategies are shown in Table 3. The optimal bid prices and profits are shown in Table 5. From Tables 4 and 5 it is observed that the proposed SFLA giving maximum power outputs and higher profits. Therefore, the bidding parameters obtained by SFLA are optimum compared to FAPSO, PSO, GA and Monte Carlo (MC) [10] method. Fig. 3 shows the variation of profit of each supplier for different methods. The convergence characteristics of proposed SFLA method, FAPSO, PSO and GA are shown in Fig. 4. From Fig. 4 it is observed that the proposed SFLA method converged in 20 iterations because of the better precise search,

**Table 3**
Generator data for IEEE 30-bus system.

| Generator | $e$ | $f$ | $P_{\min}$ (MW) | $P_{\max}$ (MW) |
|---|---|---|---|---|
| 1 | 2.0 | 0.00375 | 20 | 160 |
| 2 | 1.75 | 0.0175 | 15 | 150 |
| 3 | 1.0 | 0.0625 | 10 | 120 |
| 4 | 3.25 | 0.00834 | 10 | 100 |
| 5 | 3.0 | 0.025 | 10 | 130 |
| 6 | 3.0 | 0.025 | 10 | 130 |

**Table 4**
Optimal bidding strategies for IEEE 30-bus system.

| Generator | SFLA | FAPSO | PSO | GA | Monte Carlo [10] |
|---|---|---|---|---|---|
| | $b_j$ | $b_j$ | $b_j$ | $b_j$ | $b_j$ |
| 1 | 0.021004 | 0.001183 | 0.001092 | 0.001045 | 0.15800 |
| 2 | 0.090472 | 0.055193 | 0.050953 | 0.048786 | 0.04745 |
| 3 | 0.263450 | 0.197117 | 0.181976 | 0.174234 | 0.13099 |
| 4 | 0.054320 | 0.026303 | 0.024283 | 0.023250 | 0.02458 |
| 5 | 0.108594 | 0.078847 | 0.072791 | 0.069694 | 0.05614 |
| 6 | 0.108594 | 0.078847 | 0.072791 | 0.069694 | 0.56140 |

**Table 5**
Optimal Bid Price (MCP in $/MWh) and Profit ($) of Generators for IEEE 30-bus system.

| Generator | SFLA | | FAPSO | | PSO | | GA | | Monte Carlo [10] | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $P$ (MW) | Profit ($) | $P$ (MW) | Profit ($) | $P$ (MW) | Profit ($) | $P$ (MW) | Profit ($) | $P$ (MW) | Profit ($) |
| 1 | 160.00 | 1097.16 | 160.00 | 833.16 | 160.00 | 772.41 | 160.00 | 741.45 | 160.00 | 557 |
| 2 | 96.76 | 581.93 | 99.96 | 376.65 | 100.83 | 340.10 | 101.34 | 321.32 | 91.3 | 249 |
| 3 | 29.73 | 196.19 | 31.79 | 136.08 | 32.35 | 125.06 | 32.68 | 119.33 | 38.8 | 103 |
| 4 | 100.00 | 537.32 | 100.00 | 318.32 | 100.00 | 280.36 | 100.00 | 261.01 | 100.00 | 200 |
| 5 | 56.75 | 285.94 | 54.12 | 157.72 | 53.40 | 136.32 | 53.00 | 125.56 | 54.90 | 94 |
| 6 | 56.75 | 285.94 | 54.12 | 157.72 | 53.40 | 136.32 | 53.00 | 125.56 | 54.90 | 94 |
| MCP | 9.45 | | 7.26 | | 6.88 | | 6.69 | | 6.08 | |
| Total profit | 2984.50 | | 1979.65 | | 1790.57 | | 1694.23 | | 1297 | |

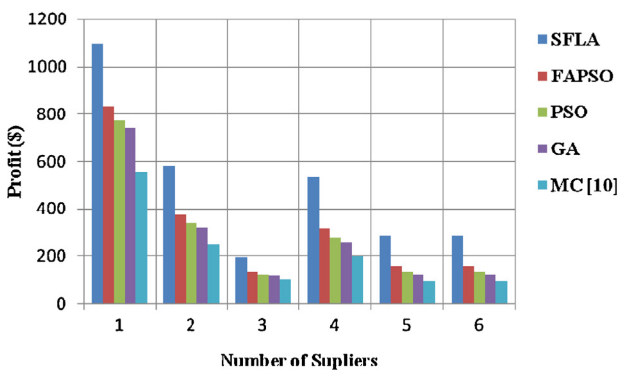


**Fig. 3.** Expected profit of suppliers for IEEE 30-bus system.

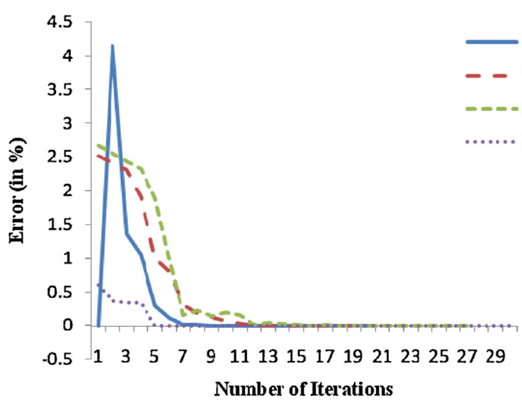


**Fig. 4.** Convergence characteristics of SFLA, FAPSO, PSO and GA for IEEE 30-bus system.

**Table 6**
Optimal bidding strategies for 75-bus Indian system.

| Generator | SFLA $b_j$ | FAPSO $b_j$ | PSO $b_j$ | GA $b_j$ |
|---|---|---|---|---|
| 1 | 0.002924 | 0.005181 | 0.002200 | 0.002944 |
| 2 | 0.004509 | 0.007623 | 0.003232 | 0.004774 |
| 3 | 0.002369 | 0.003073 | 0.006976 | 0.003918 |
| 4 | 0.006296 | 0.006428 | 0.006762 | 0.002844 |
| 5 | 0.334051 | 0.369391 | 0.134368 | 0.196915 |
| 6 | 0.011553 | 0.013333 | 0.011002 | 0.005410 |
| 7 | 0.019105 | 0.011011 | 0.006162 | 0.012133 |
| 8 | 0.004908 | 0.011473 | 0.009800 | 0.004973 |
| 9 | 0.010374 | 0.012481 | 0.008323 | 0.004177 |
| 10 | 0.006258 | 0.003031 | 0.003392 | 0.003222 |
| 11 | 0.005537 | 0.005369 | 0.002952 | 0.003222 |
| 12 | 0.007409 | 0.004972 | 0.005573 | 0.003063 |
| 13 | 0.004727 | 0.001514 | 0.002035 | 0.002964 |
| 14 | 0.002403 | 0.004820 | 0.005630 | 0.002665 |
| 15 | 0.006110 | 0.005822 | 0.002529 | 0.003640 |

where as FAPSO, PSO and GA are converged in 22, 27 and 30 iterations respectively. Therefore the proposed method converges fast compared to FAPSO, PSO and GA.

### 5.2. Practical 75-bus Indian system [26]

75-bus Indian system consists of 15 suppliers, who supply electricity to aggregate load. $Q_o$ is 1000 and $K$ is 10, considered for aggregated load. Bidding coefficients, generator output, MCP and profit of suppliers are calculated using SFLA, shown in Tables 6 and 7. Fig. 5 shows the variation of profit of each supplier for different methods. Fig. 6 shows the convergence characteristics of different methods. It is observed that proposed SFLA converged

**Table 7**
Optimal bid price (MCP in Rs/MWh) and profit (Rs) of generators for 75-bus Indian system.

| Generator | SFLA | | FAPSO | | PSO | | GA | |
|---|---|---|---|---|---|---|---|---|
| | $P$ (MW) | Profit (Rs) | $P$ (MW) | Profit (Rs) | $P$ (MW) | Profit (Rs) | $P$ (MW) | Profit (Rs) |
| 1 | 333.48 | 485.76 | 222.0 | 182.5 | 471.3 | 160.02 | 171.7 | 119.7 |
| 2 | 164.14 | 178.30 | 89.2 | 41.6 | 175.4 | 25.6 | 56.6 | 22.9 |
| 3 | 280.00 | 256.98 | 205.2 | 46.4 | 74.1 | 27.5 | 62.6 | 23.0 |
| 4 | 165.20 | 304.62 | 199.2 | 198.3 | 172.6 | 158.8 | 100 | 99.8 |
| 5 | 3.44 | 6.74 | 4.0 | 4.4 | 10.3 | 3.7 | 3.4 | 3.5 |
| 6 | 64.92 | 85.93 | 53.2 | 30.1 | 54.2 | 24.3 | 52.7 | 22.5 |
| 7 | 39.52 | 50.16 | 160 | 243.9 | 160 | 225.7 | 80 | 149.8 |
| 8 | 170.15 | 211.80 | 75.8 | 51.6 | 77.2 | 43.5 | 73.5 | 40.2 |
| 9 | 75.19 | 105.44 | 60.9 | 38.5 | 77.7 | 37.6 | 74.3 | 34.5 |
| 10 | 137.44 | 205.82 | 180 | 113.2 | 180 | 92.7 | 90 | 57.1 |
| 11 | 163.46 | 252.61 | 188.2 | 132.8 | 209 | 116.7 | 104.5 | 73.3 |
| 12 | 156.58 | 325.54 | 305.8 | 320.9 | 252.5 | 257.1 | 225.4 | 233.1 |
| 13 | 226.38 | 408.14 | 885.6 | 18.5 | 603.1 | 198.1 | 202.6 | 182.2 |
| 14 | 250.00 | 571.30 | 250 | 371.3 | 250 | 343.0 | 125 | 189.2 |
| 15 | 270.00 | 747.60 | 120.3 | 57.8 | 232.1 | 37.6 | 77.0 | 32.39 |
| MCP | 8.60 | | 7.80 | | 7.68 | | 7.56 | |
| Total profit | 4196.80 | | 1852.41 | | 1752.6 | | 1283.89 | |

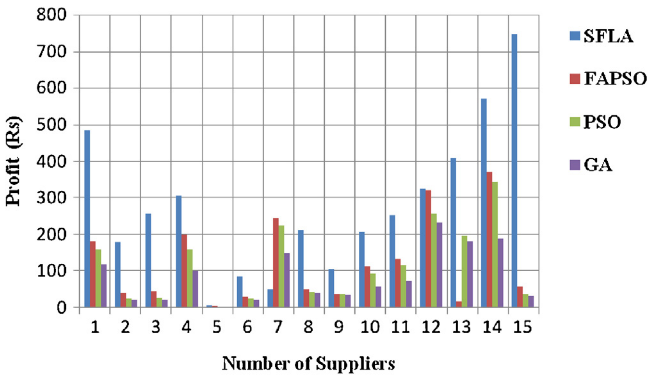


**Fig. 5.** Expected profit of suppliers for practical 75-bus Indian system

**Table 8**
Performance comparison of different approaches for IEEE 30-bus system.

| | SFLA | FAPSO | PSO | GA |
|---|---|---|---|---|
| Total profit ($) | | | | |
| Best ($) | 2984.50 | 1979.65 | 1790.57 | 1694.23 |
| Worst ($) | 2792.34 | 1754.72 | 1574.85 | 1464.27 |
| Ave. ($) | 2888.42 | 1867.18 | 1682.71 | 1579.25 |
| PD (%) | 0.064 | 0.113 | 0.120 | 0.135 |
| Average c.p.u. time (s) | 0.251 | 4.21 | 6.24 | 12.28 |

in 24 iterations, whereas FAPSO, PSO and GA are converged in 28, 47 and 58 iterations respectively. Therefore, even if the size of the system increases still proposed method shows better convergence characteristics because, SFLA combines the benefits of the both the Genetic-based Memetic Algorithm (MA) and the social behavior-based PSO algorithm.

The superiority of the SFLA approach is demonstrated through comparison of simulation results with FAPSO, PSO and GA. Due to the randomness of the evolutionary algorithms, their performance cannot be judged by the result 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 SFLA, FAPSO, PSO and GA random in nature therefore the bidding data was executed 20 times for all the approaches. The best, worst, average values, total profit and PD for the given data are tabulated in Tables 8 and 9 for IEEE 30-bus and practical 75 bus Indian system respectively. The Percentage Deviation (PD) is computed as follows:

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

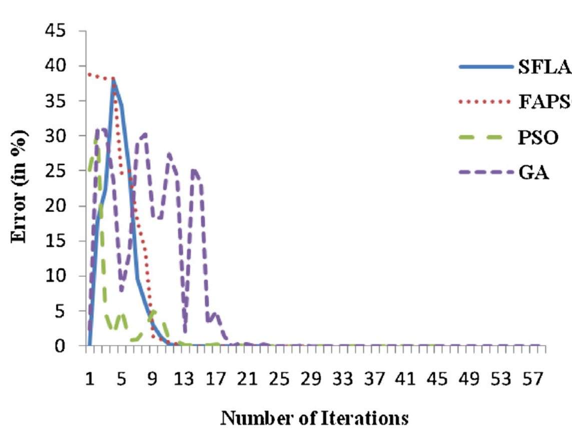


**Fig. 6.** Convergence characteristics of SFLA, FAPSO, PSO and GA for 75-bus Indian system.

**Table 9**
Performance comparison of different approaches for 75-bus Indian system.

| | SFLA | FAPSO | PSO | GA |
|---|---|---|---|---|
| Total profit (Rs) | | | | |
| Best (Rs) | 4196.80 | 1852.41 | 1752.6 | 1283.89 |
| Worst (Rs) | 4092.16 | 1743.28 | 1627.34 | 1092.06 |
| Ave. (Rs) | 4144.48 | 1797.84 | 1689.97 | 1187.97 |
| PD (%) | 0.024 | 0.058 | 0.071 | 0.149 |
| Average c.p.u. time (s) | 0.4235 | 8.342 | 10.725 | 18.462 |

Tables 8 and 9 show that the PD is minimum for the proposed SFLA method compared to FAPSO, PSO and GA, for the IEEE 30-bus system as well as 75-bus Indian system and it is clearly observed that the optimal bidding strategies obtained by SFLA giving higher profits compared to FAPSO, PSO and GA. In addition to that, SFLA shows good consistency by keeping small variation between the best and worst solution. In other words, the simulation results show that, the SFLA algorithm converges to global solution has a shorter c.p.u. time and small percentage deviation because, in each memeplex a local search algorithm is applied to improve only the frog with the worst fitness (not all frogs) in each cycle. As a result, frogs tend to move toward the best position, which avoids premature convergence and permits a faster convergence.

## 6. Conclusion

In this paper Shuffled Frog Leaping Algorithm (SFLA) is proposed for the first time, to solve the bidding strategies for generation companies in a pool based electricity market. It is a memetic meta-heuristic that is based on 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 Memetic Algorithm (MA) and social behavior-based PSO algorithm with such characteristics as simple concept, fewer parameters adjustment, prompt formation, great capability in global search and easy implementation. The effectiveness of the proposed SFLA has been tested on IEEE 30-bus system and practical 75-bus Indian system. The results are compared with FAPSO, PSO and GA. The numerical results reveal the superiority of the proposed SFLA compared to FAPSO, PSO and GA with respect to total profit and convergence of c.p.u. time. Therefore, the proposed algorithm produces more profit and converges very rapidly so that it can be used for real-time applications.

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