

The role of basic, modified and hybrid shuffled frog leaping algorithm on optimization problems: a review

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Abstract Shuffled frog leaping algorithm (SFLA) is a meta-heuristic to handle different large-scale optimization problems. SFLA is a population-based algorithm that combines the advantages of memetic algorithm and particle swarm optimization. This paper compares previous researches on SFLA and its effectiveness, with the most applied optimization algorithms reviewed and analyzed. Based on the literature, many efforts by previous researchers on SFLA denote the next generations of basic SFLA with diverse structures for modified SFLA or hybrid SFLA. As well, an attempt is made to highlight these structures, their enhancements and advantages. Moreover, this paper considers top improvements on SFLA for solving multi-objective optimization problems, enhancing local and global exploration, avoiding being trapped into local optima, declining computational time and improving the quality of the initial population. The measured enhancements in SFLA are based on the statistical results obtained from 89 published papers and by considering the most common and effective modifications done by a large number of researchers. Finally, the quantitative validations address the SFLA as a robust algorithm employed in various applications which outperforms the other optimization algorithms.

Keywords Shuffled frog leaping algorithm · Optimization · Modification · Hybridization · Application · Comparison · Review

1 Introduction

The optimization problem is to provide the finest solution from all feasible solutions based on the defined specified objectives. Multi-objective optimization problems are common problems which have two or more objectives that regularly conflict with each other and have to be minimized (or maximized) concurrently. A vector of decision variables is provided as a result by optimizing the objective functions and satisfying the predefined constraints (Niknam et al. 2011a).

There are two types of algorithms for solving different optimization problems: traditional and nontraditional algorithms. Traditional algorithms try to present a local optima solution, while the solution provided by nontraditional algorithms is only an approximation based on extrinsic model or objective function. Traditional algorithms, such as Taguchi method, nonlinear programming, geometric programming, and dynamic programming, try to find a near-optimal solution. These kinds of algorithms generally do not succeed in handling different complex problems, particularly including nonlinear objective functions or those including numerous local optima, and may reduce the convergence rate (Rao and Savsani 2012). Nontraditional or evolutionary algorithms could overcome these problems. These algorithms are based on accidental search that emulates the natural biological evolution and the social behavior of the genus (Rameshkhah et al. 2010). In recent years, these kinds of algorithms have been found to be sufficiently robust and widely employed by researchers to solve nonlinear, highly dimensional and com-

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plex optimization problems that provide near-optima solutions (Rao 2011).

Nowadays, various powerful evolutionary optimization algorithms have been designed to handle various complex engineering problems. Some of the most functional basic algorithms with brief description are as follows:

- Genetic algorithm (GA) is a heuristic search based on the national genetics, proposed by Holland (1973).
- Memetic algorithm (MA) is a genetic-based algorithm and based on cultural evolution, proposed by Richard (1976).
- Simulated annealing (SA) works according to the theory of explosion grenade, proposed by Kirkpatrick et al. (1983).
- Ant colony optimization (ACO) works according to the theory of foraging behavior of ants looking for food, by Dorigo (1992).
- Particle swarm optimization (PSO) works according to the choreography of a bird flock, proposed by Eberhart and Kennedy (1995).
- Shuffled frog leaping algorithm (SFLA) works according to the theory of frogs' communication, proposed by Eusuff and Lansey (2003).
- Artificial bee colony (ABC) works according to the theory of foraging behavior of a honey bee, proposed by Karaboga (2005).

Among these algorithms, SFLA which is proposed to look for global optimal solution through a heuristic function (Eusuff and Lansey 2003) is efficient in a wide range of multi-objective and complex optimization problems. In the next section, the basic concepts and structure of SFLA and its next generations to make it more powerful are described in detail.

2 Overview of SFLA

The SFLA as a population-based algorithm simulates the behavior of frogs located in swamps seeking around for the optimum location of food. The algorithm utilizes local search and global search capabilities (Shayanfar et al. 2010a,b; Eusuff et al. 2006) and integrates the advantages of the MA and PSO algorithms (Rameshkhah et al. 2010). The main advantage of MA is that it passes information among all population, while in GA there is interaction only between parent–sibling. On the other hand, PSO algorithm is more effective and has a fast convergence rate. Also, all its particles tend to converge to the best global solution and provide a near-optimal solution with high convergence speed (Rao 2011). Moreover, unlike MA, the PSO algorithm needs a simple coding process. Hence, SFLA profits from the advan-

tages of MA and PSO and has better performance on the global search to find an optimal solution.

The population in SFLA, which is a memetic meta-heuristic, contains a set of frogs (solutions) classified into different memeplexes with various frogs' cultures. SFLA does a local exploration using PSO algorithm in each memeplex simultaneously. The frogs are shuffled and reorganized into new memeplexes to guarantee global exploration (Wang and Fang 2011). The shuffling processes and local search continue until the stopping criteria are satisfied (Rameshkhah et al. 2010). Memetic evolution enhances individual memetics quality. The local search in SFLA transfers memetic among the individuals and the shuffling process transfers memetic amongst the global (Rao 2011). It is shown that SFLA has better performance of the global search in large generation size of memeplexes that needs high computation time. In addition, the shuffling process enhances the quality of memetics based on different memeplexes with different cultures. Exchanging the information between local and global search results would guarantee the algorithm's flexibility and robustness (Amiri et al. 2009).

Alternatively, SFLA is integration of random and determinacy approaches (Eusuff et al. 2006; Rao 2011). The determinacy approach exchanges messages in the algorithm successfully and random approach guarantees the robustness and flexibility of the algorithm (Rao 2011).

3 Basic SFLA

The basic SFLA meta-heuristic technique is structured into three main phases (Niknam et al. 2011b): initialize, evaluation, and shuffling. In the initialize phase, f frogs are selected randomly. In the evaluation phase, the frogs are sorted based on descending order of fitness value. Then, the sorted frogs are partitioned into m groups (memeplexes) which can perform the local search independently. During the local search, frogs of each memeplex improve to find a better fitness value. It is feasible to raise the fitness value of a high-quality frog and reduce the fitness value of a low-quality frog based on the predefined objective. Shuffling phase is for enhancing the global search (Zhen et al. 2009). In this phase, after accomplishing evolution, the memeplexes are shuffled. The frogs are optimized globally and generate new memeplexes (Amiri et al. 2009). The processes of evolution and shuffling continue several times until the best solution is found. The basic SFLA's diagram is shown in Fig. 1.

Consequently, SFLA is developed based on four key parameters: the number of memeplexes (m), the number of frogs in each memeplex (n), the number of frogs in population (p), the number of evolution or iterations between two consecutive shuffling (s), and the number of maximum iteration (N).

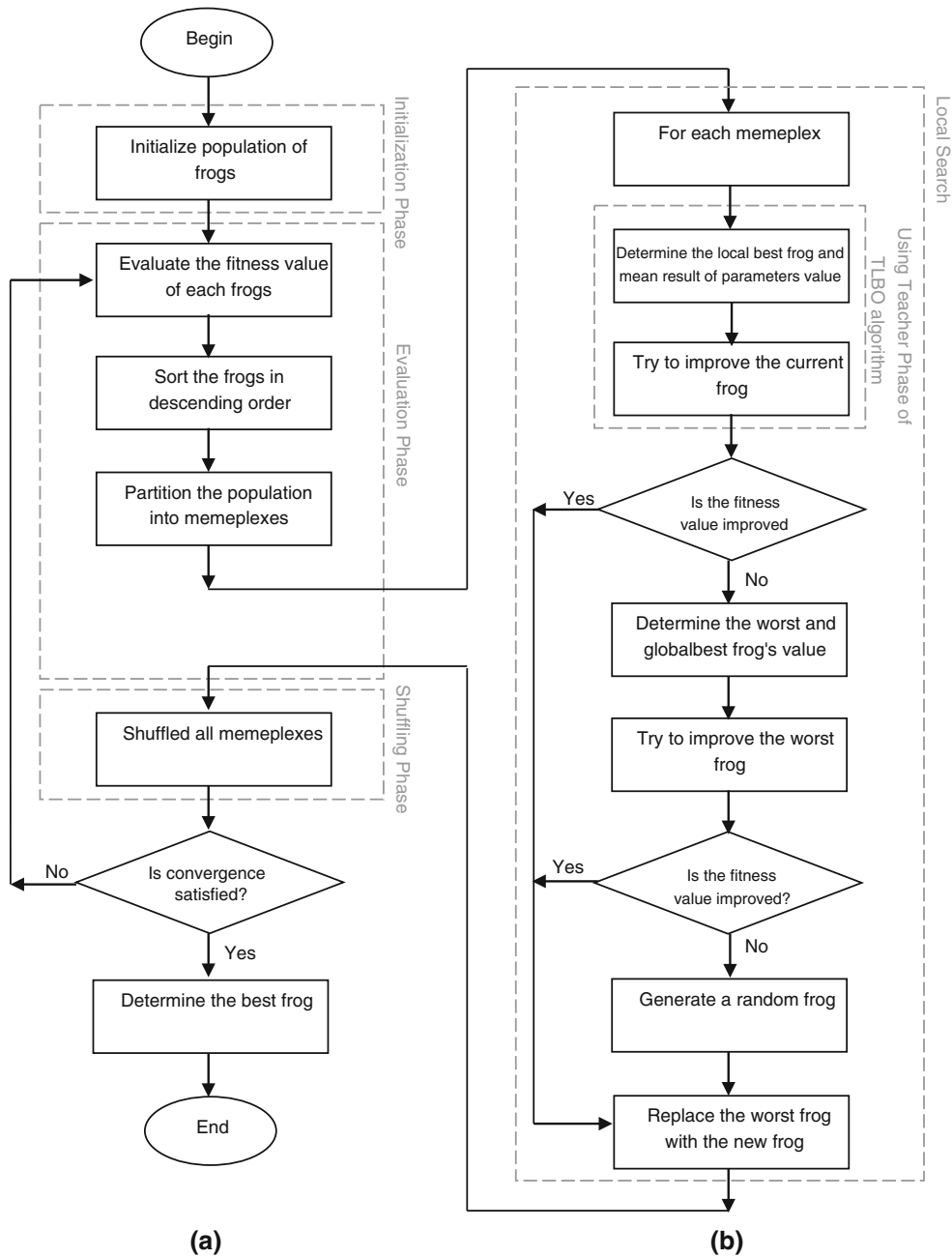


Fig. 1 **a** The proposed SFL-TLBO algorithm’s main diagram, **b** local search for each memeplex

The population of frogs is shown as

$$X = \{x_1, x_2, \dots, x_p\}, \tag{1}$$

and the frog i is presented as

$$x_i = \{x_i^1, x_i^2, \dots, x_i^h\}, \tag{2}$$

where h indicates the number of decision variables (parameters) in a frog (solution).

To handle multi-objective optimization problems with several conflicting objectives which have to be consid-

ered simultaneously, the main objective function should be defined as follows (Niknam et al. 2011b):

$$(\min/\max) F = [f_1(x), f_2(x), \dots, f_k(x)]^T, \tag{3}$$

while quality constraint $g_i(x)$ and inequality constraint $h_i(x)$ are satisfied:

$$g_i(x) < 0 \quad i = 1, 2, \dots, N_1$$

$$h_i(x) = 0 \quad i = 1, 2, \dots, N_2,$$

where k shows the number of objective functions, $f_i(x)$ is i th objective function, and N_1 and N_2 are the number of equality and inequality constraints respectively,

The steps of basic SFLA are given as follows:

1. Initialize a random population of p solution (frogs).
2. Calculate the fitness function (position) for each frog (solution's fitness value).
3. Sort the frogs based on their fitness values (in descending order).
4. Partition the population into m groups (memeplexes) as follows: allocate the frogs to the groups according to the fitness values. The first frog with the highest value moves to the first group, the second highest frog moves to the second group . . . the m th highest frog moves to the last group. Then, $m + 1$ th frog moves to the first group again. These operations continue until the last frog is allocated to a group. Finally, each group contains n frogs. Thus, $p = n \times m$.
5. For each group (memeplex), follow steps 5.1–5.2.
 - 5.1. Select the frogs with the worst position x_w and best position x_b .
 - 5.2. For a predefined number of times (s), improve the worst position by following steps 5.2.1–5.2.7.
 - 5.2.1. Perform a local search for each group (memeplex) using the following equation,

$$x'_i = x_i + r \times (x_b - x_w) \quad i = 1, 2, \dots, m, \quad (4)$$

where x'_i indicates a new position in the next iteration and r is a random number between 0 and 1.
 - 5.2.2. If $x'_i > x_i$, then go to step 5.2.7.
 - 5.2.3. Select the global best frog position x_g .
 - 5.2.4. Apply global search using the following equation:

$$x'_i = x_i + r \times (x_g - x_w). \quad (5)$$
 - 5.2.5. If $x'_i > x_i$, then go to step 5.2.7.
 - 5.2.6. Generate a new frog x'_i randomly.
 - 5.2.7. Replace frog x_i with x'_i .
6. Shuffle all the memeplexes.
7. Check the termination criteria. If it has happened, then stop; else, continue from step 2.

The termination criteria for the algorithm could be satisfied by one of the following three conditions:

1. The value of the main objective function F reaches an acceptable and optimum value.

2. The number of iterations gains to a predefined value (N); it varies for different number of dimensions in a problem.
3. During several consecutive iterations, no progress could be seen in the value of the main objective function F .

Table 1 indicates various studies done based on basic SFLA to attain an effective optimization result in a variety of applications. In addition, Table 1 gives some information about the comparison results between the proposed SFLA and other common optimization techniques on accuracy, convergence rate, computational time, and performance.

3.1 Generations of SFLA

Although basic SFLA applied PSO as a local exploration and merged information from parallel local explorations to come up to a global exploration, it has some limitations in one or the other aspects. For example, being trapped in local optimum reported by many researchers is a problem in basic SFLA. Also, as the worst frog's position in local exploration will never jump over the best one, the convergence speed will be slowed down and cause premature convergence. Consequently, in recent years there are some studies to overcome these problems of basic SFLA.

On the other hand, some of the researches are ongoing to enhance the basic SFLA performances. For example, they improve the accuracy of the solution, the diversity of the search space vector, the algorithm's searching capacity or enhance the local search capability. In addition, some studies try to initialize a high-quality population with an assured level of diversity to improve solution quality and convergence rate.

Alternatively, there are some studies related to SFLA for solving continuous, combinatorial and multi-objective optimization problems with imprecise objective functions, while basic SFLA has some limitations to find the optimum solution.

Accordingly, researchers continue to improve the performance of basic SFLA. Enhancement is done either on the algorithm by modification of SFLA (MSFLA) or hybridization of SFLA (HSFLA). In MSFLA, the algorithm is improved by applying or replacing new functions, heuristics or factors. In HSFLA, basic SFLA is integrated with other evolutionary algorithms.

4 Modified SFLA

As a consequence of the continuous feature of SFLA, it is difficult to solve large-scale, complicated and combinatorial optimization problems (Li and Wang 2011). To handle these kinds of optimization problems and improve the performance, some previous works proposed different structures for modified SFLA (MSFLA).

Table 1 Comparison result between the proposed SFLA and other published algorithms

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
1	Eusuff and Lansay (2003)	SFLA	N/A	N/A	SFLA > GA, SA	SFLA > GA, SA	Water distribution network optimization problems	Previous research work comparisons: $p = 510$, $m = 30$, $n = 17$, $s = 17$, $N = 100$
2	Eusuff et al. (2006)	SFLA	SFLA > GA	SFLA > GA	SFLA > GA	SFLA > GA	Water distribution network optimization problems	Previous research work comparisons: $p = N/A$, $100 < m < 150$, $30 < n < 100$, $20 < s < 30$, $N = N/A$
3	Rao (2011)	SFLA	ABC > PSO, GA, MA > SFLA	ABC > PSO > MA > GA; SFLA > GA	SFLA > GA	MA > GA	Classification problems	Previous research work comparisons: $p = 20$, $m = 5$, $n = 4$, $s = N/A$, $N = 50$
4	Jahani et al. (2011)	SFLA	N/A	N/A	N/A	SFLA > PSO, GA	Electrical power system optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
5	Banati and Mehta (2012)	SFLA	N/A	MA > GA; PSO > MA; SFLA > PSO	N/A	SFLA > PSO, MA, GA	N/A	Benchmark comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
6	Zhen et al. (2007)	SFLA	N/A	SPSO > SFLA, PSO	SPSO > PSO > SFLA	SPSO > SFLA, PSO	Continuous optimization problem	Previous research work comparisons: $p = 200$, $m = 10$, $n = 20$, $s = 15$, $N = 200$
7	Jahani et al. (2010)	SFLA	N/A	N/A	N/A	SFLA > GA, PSO	Electrical power system optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
8	Rao (2011)	SFLA	SFLA > ABC, SA, HS, PSO	SFLA > ABC, SA, HS, PSO, GA	N/A	N/A	N/A	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
9	Nejad et al. (2011)	SFLA	SFLA > GA	SFLA > GA	SFLA > GA	SFLA > GA	Electrical power system optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
10	Tavakolan (2011)	SFLA	N/A	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	Time-cost trade-off construction management problem; time-cost-resource optimization problem; resource scheduling problem	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
11	Tavakolan and Ashuri (2012)	SFLA	N/A	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	SFLA > GA, PSO, ACO	Time-cost trade-off construction management problem; time-cost-resource optimization problem; resource scheduling problem	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
12	Yammani et al. (2012)	SFLA	N/A	N/A	N/A	SFLA > GA	Optimization of placement in distribution network	Previous research work comparisons: $p = 32$, $m = 4$, $n = 8$, $s = N/A$, $N = 100$
13	Luo et al. (2008)	SFLA	N/A	N/A	N/A	SFLA > GA	Traveling salesman problem	Benchmark comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
14	Amiri et al. (2009)	SFLA	SFLA > GA, SA, TS, ACO	SFLA > GA, SA, TS, ACO	SFLA > GA, SA, TS, ACO	SFLA > GA, SA, TS, ACO	Data clustering problem	Previous research work comparisons: $p = 150$, $m = 5$, $n = 30$, $s = 50$, $N = 1,000$
15	Anita and Raglend (2012)	SFLA	SFLA > ICGA, LR	SFLA > ICGA, LR	SFLA > ICGA, LR	SFLA > ICGA, LR	Unit commitment scheduling problem	ICGA: integer coded GA; LR: Lagrangian; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
16	Chen (2009)	SFLA	N/A	N/A	N/A	SFLA > EP, GA	Combined economic emission dispatch	EP: evolutionary programming; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
17	Chen et al. (2009)	SFLA	SFLA > PSO	N/A	N/A	SFLA > PSO	Dynamic power flow optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
18	Duan and Pan (2010)	SFLA	SFLA > ACO, GA	N/A	N/A	SFLA > ACO, GA	Lot-streaming flow shop scheduling problem	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
19	Eghbal et al. (2011)	SFLA	SFLA > PSO, GA	SFLA > PSO, GA	N/A	N/A	Distribution expansion planning problem	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
20	Eusuff (2004)	SFLA	SFLA > GA	N/A	N/A	SFLA > GA	Water distribution network optimization problems	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
21	Li (2009)	SFLA	SFLA > GA, PSO	SFLA > GA, PSO	N/A	N/A	Reactive power flow optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
22	Rameshkhah (2011)	SFLA	SFLA > PSO	N/A	N/A	N/A	Clustering problem in power systems	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
23	Shirvani et al. (2012a)	SFLA	SFLA > CPSS	N/A	N/A	N/A	Optimization of PID power system stabilizer	CPSS: conventional power system stabilizer; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
24	Shirvani et al. (2012b)	SFLA	SFLA > GA	N/A	N/A	N/A	Unified power flow controllers in electrical power systems	Previous research work comparisons: $p = N/A$, $m = 2$, $n = N/A$, $s = 2$, $N = 20$
25	Lin et al. (2007)	SFLA	SFLA > GA, SA, TS	SFLA > GA, SA, TS	N/A	N/A	Water distribution network optimization problems	Benchmark comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
26	Liping et al. (2012)	SFLA	SFLA > WW, SM, L4L, LUC	N/A	N/A	SFLA > WW, SM, L4L, LUC	Production planning problem	WW: Wagner–Whitin; SM: Silver–Meal; L4L: Lot–4–Lot; LUC: least unit cost; previous research work comparisons: $p = 100$, $m = 10$, $n = 10$, $s = 5$, $N = 2,000$
27	Luo (2012)	SFLA	N/A	N/A	N/A	SFLA > GAS	Logistics distribution vehicle routing problem/traveling salesman problem (TSP)	GAS: hybrid GA-ACO-SA; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
28	Pasha and Lansley (2009)	SFLA	N/A	N/A	N/A	SFLA > random search technique, exact data	Water distribution network optimization problems	Experimental data: $p = 3,500$, $m = 50$, $n = 70$, $s = 10$, $N = N/A$
29	Zhang and Wang (2010)	SFLA	SFLA > PSO	SFLA > PSO	N/A	N/A	Viewpoint selection in visualization of 3D datasets	Previous research work comparisons: $p = 12$, $m = 3$, $n = 4$, $s = 6$, $N = 30$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
30	Li and Wang (2011)	MSFLA	N/A	MSFLA > SFLA, PSO, GA	MSFLA > SFLA, PSO, GA	N/A	Traveling salesman problem	Previous research work comparisons: $p = 100$, $m = 5$, $n = 20$, $s = 10$, $N = N/A$
31	Niknam et al. (2012)	MSFLA	N/A	N/A	N/A	MSFLA > PSO-HBMO, PSO-ACO, DPSO-ACO	Feeder reconfiguration problem in distribution networks	HBMO: honey bee mating optimization; DPSO: discrete PSO; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
32	Malekpour et al. (2012)	MSFLA	MSFLA > SFLA	N/A	N/A	N/A	Volt/Var control of distribution system	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
33	Pan et al. (2010)	MSFLA	N/A	N/A	N/A	MSFLA > GA, HGA, ACO, TA, NEH	Flexible job/flow shop scheduling problem	HGA: Hybrid GA; TA: threshold accepting algorithm; NEH: Nawaz-Enscore-Ham algorithm; previous research work comparisons: $p = 20$, $m = 4$, $n = 5$, $s = N/A$, $N = N/A$
34	Baghmisheh et al. (2011)	MSFLA	N/A	MSFLA > SFLA, BGA, DPSO	SFLA > MSFLA; MSFLA > BGA, DPSO	MSFLA > SFLA, BGA, DPSO (On high dimensional functions)	Discrete/real-valued optimization problems	BGA: binary GA; DPSO: discrete PSO; previous research work comparisons: $p = 60$, $m = 6$, $n = 10$, $s = 10$, $N = 20,000$
35	Pu et al. (2011)	MSFLA	N/A	MSFLA > SFLA, PSO	MSFLA > SFLA, PSO	MSFLA > SFLA, PSO	Autonomous flight control optimization	Previous research work comparisons: $p = 20$, $m = 4$, $n = 5$, $s = 5$, $N = 30$
36	Shayanfar et al. (2010a, b)	MSFLA	N/A	MSFLA > SFLA, PSO	N/A	MSFLA > SFLA, PSO	Electrical power system optimization	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
37	Li et al. (2012a, b)	MSFLA	N/A	N/A	N/A	MSFLA > GA, PSO-SA, GA, MATSLO, PSO-TS, MOGA, KBACO	Flexible job shop scheduling problems	MOGA : multi-objective GA; KBACO: knowledge-based ACO; benchmark comparisons: $p = 100$, $m = 20$, $n = 5$, $s = 50$, $N = N/A$
38	Niknam et al. (2011a)	MSFLA	MSFLA > GA, PSO, SFLA	MSFLA > GA, PSO, SFLA	MSFLA > GA, PSO, SFLA	MSFLA > GA, PSO, SFLA	Feeder reconfiguration problem in distribution networks	Previous research work comparisons: $p = 10$, $m = 10$, $n = 1$, $s = 10$, $N = 100$
39	Zhen et al. (2009)	MSFLA	MSFLA > SFLA, PSO	MSFLA > SFLA, PSO	N/A	MSFLA > SFLA, PSO	Continues optimization problem	Previous research work comparisons: $p = N/A$, $m = 10$, $n = N/A$, $s = 50$, $N = 100$
40	Chittinemi et al. (2011a)	MSFLA	MSFLA > SFLA	MSFLA > SFLA	N/A	MSFLA > SFLA	Classification problems	Previous research work comparisons: $p = 20$, $m = 5$, $n = 4$, $s = N/A$, $N = N/A$
41	Alghazi et al. (2012)	MSFLA	MSFLA > GA, SA	MSFLA > GA, SA	MSFLA > GA, SA	MSFLA > GA, SA	Finance-based scheduling problem	Previous research work comparisons: $p = 2,000$, $m = 20$, $n = 100$, $s = 15$, $N = 500$
42	Elbeltagi et al. (2007)	MSFLA	N/A	N/A	MSFLA > SFLA, GA	N/A	Project scheduling problem	Benchmark comparisons: $p = 200$, $m = 20$, $n = 10$, $s = 10$, $N = N/A$
43	Li et al. (2010)	MSFLA	N/A	N/A	N/A	MSFLA > NGSA-II, SPEA-II, dynamic programming	Reservoir flood control problem	SPEA : strength pareto evolutionary algorithm; NSGA-II: non-dominated sort GA; previous research work comparisons: $p = 200$, $m = 20$, $n = 10$, $N = 500$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
44	Liu et al. (2011)	MSFLA	N/A	MSFLA > MOPSO, NSGA-II, SPEA-II	MSFLA > MOPSO, NSGA-II, SPEA-II	MSFLA > MOPSO, NSGA-II, SPEA-II	Biclustering problem	MOPSO: multi-objective PSO; previous research work comparisons: $p = 60, m = 6, n = 10, s = N/A, N = 50,000$
45	Niknam et al. (2011b)	MSFLA	N/A	MSFLA > GA, PSO	N/A	N/A	Electrical power system optimization	Previous research work comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$
46	Wang et al. (2011)	MSFLA	N/A	MSFLA > PSO	N/A	MSFLA > PSO	No_idle permutation flow shop scheduling problems	Previous research work comparisons: $p = 100, m = 20, n = 5, s = N/A, N = N/A$
47	Wang and Fang (2011)	MSFLA	N/A	MSFLA > SFLA, PSO	N/A	MSFLA > SFLA, PSO	Multi-mode resource-constrained project scheduling problem	Benchmark comparisons: $p = 100, m = 10, n = 10, s = 2, N = N/A$
48	Jafari et al. (2012)	MSFLA	N/A	N/A	MSFLA > GA, ICA	MSFLA > GA, ICA	Optimization of analog integrated circuits sizing	Previous research work comparisons: $p = 100, m = N/A, n = N/A, s = 100, N = N/A$
49	Huynh (2008)	MSFLA	N/A	MSFLA > GA, ICA	N/A	MSFLA > GA, ICA	Optimization of PID power system stabilizer	Previous research work comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$
50	Li et al. (2012a,b)	MSFLA	N/A	N/A	N/A	MSFLA > GA	Continuous optimization problem	Previous research work comparisons: $p = 200, m = 20, n = 10, s = 10, N = N/A$
51	Fang and Wang (2012)	MSFLA	MSFLA > GA	N/A	N/A	MSFLA > GA, HGA, TS, SA	Resource-constrained project scheduling problem	Previous research work comparisons: $p = 300, m = 10, n = 30, s = N/A, N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
52	Niknam et al. (2011c)	MSFLA	MSFLA > SFLA, PSO	N/A	N/A	MSFLA > SFLA, PSO	Electric energy necessitate optimal economic dispatch	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
53	Wang and Di (2010)	MSFLA	N/A	N/A	N/A	MSFLA > original 3-D Otsu thresholding	Knapsack problem	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
54	Liu et al. (2012)	MSFLA	N/A	MSFLA > PSO, SFL, DPSO	N/A	MSFLA > PSO, SFL, DPSO	Biclustering problem	DPSO: discrete PSO; previous research work comparisons: $p = 60$, $m = 10$, $n = 6$, $s = 10$, $N = N/A$
55	Chen et al. (2011a)	MSFLA	MSFLA > PSO, GA	MSFLA > PSO, GA	N/A	MSFLA > PSO, GA	Job-shop scheduling problem	Benchmark comparisons: $p = 200$, $m = 10$, $n = 20$, $s = 10$, $N = 1,000$
56	Chen et al. (2011b)	MSFLA	MSFL > GA	N/A	N/A	N/A	Component sequencing problem	Previous research work comparisons: $p = 240$, $m = 15$, $n = 16$, $s = 10$, $N = 30$
57	Chittineni et al. (2011b)	MSFLA	MSFL > CLON-ALG, SFLA	MSFL > CLONALG, SFLA	N/A	MSFL > CLON-ALG, SFLA	Unsupervised data clustering	Benchmark comparisons: $p = 20$, $m = 5$, $n = 4$, $s = 30$, $N = 300$
58	Kimiyağhalam (2012)	MSFLA	MSFLA > SFLA, GA	MSFLA > SFLA, GA	N/A	N/A	Detection of fault location in distribution networks	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
59	Huynh and Nguyen (2009)	MSFLA	N/A	N/A	N/A	MSFLA > exact data	Fuzzy controllers/ball and beam system	Previous research work comparisons: $p = 20$, $m = 4$, $n = 5$, $s = 8$, $N = 500$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
60	Kavousifard and Samet (2011)	MSFLA	MSFLA-ANN > ANN	N/A	N/A	N/A	Optimization of ANN model for prediction of power system load	ANN: artificial neural network; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
61	Li et al. (2011a)	MSFLA	N/A	N/A	MSFLA > HC, GA, HGA, ACO	N/A	Logistics distribution vehicle routing problem → traveling salesman problem (TSP)	HC: high climbing algorithm; previous research work comparisons; $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
62	Lin et al. (2012)	MSFLA	MSFLA > SFLA	MSFLA > SFLA	N/A	N/A	RNA secondary structure prediction/biological system	Previous research work comparisons: $p = 50$, $m = 5$, $n = 10$, $s = 10$, $N = 200$
63	Lin et al. (2011)	MSFLA	MSFLA > SFLA	MSFLA > SFLA	N/A	N/A	RNA secondary structure prediction/biological system	Previous research work comparisons: $p = 50$, $m = 5$, $n = 10$, $s = 50$, $N = 200$
64	Perez et al. (2012)	MSFLA	MSFLA > DE, PSO, GA, SFLA	MSFLA > DE, PSO, GA, SFLA	N/A	N/A	Optimization of parameters of induction machines	DE: differential evolution; previous research work comparisons: $p = 100$, $m = 10$, $n = 10$, $s = 5$, $N = 30$
65	Gomez-Gonzalez (2013)	MSFLA	MSFLA > PAMP, PSO, GA	N/A	N/A	N/A	Optimization of parameters of induction machines	PAMP: power asynchronous machine params (a classical parameter estimation method); previous research work comparisons: $p = 60$, $m = 10$, $n = 6$, $s = 5$, $N = 50$
66	Sardou et al. (2012)	MSFLA	MSFLA > SFLA, GA	MSFLA > SFLA, GA	N/A	N/A	Optimization of placement in distribution network	Previous research work comparisons: $p = 100$, $m = 20$, $n = 5$, $s = 6$, $N = 50$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
67	Zhijin et al. (2008)	MSFLA	MSFLA > GA, PSO	N/A	N/A	N/A	Multi-user detection problem–telecommunication	Previous research work comparisons: $p = 30$, $m = 3$, $n = 10$, $s = N/A$, $N = N/A$
68	Xu et al. (2012)	MSFLA	N/A	N/A	MSFLA > GA, discrete PSO	N/A	Networked two-layer learning control systems	Previous research work comparisons: $p = 200$, $m = 20$, $n = 10$, $s = N/A$, $N = N/A$
69	Sayedi et al. (2012)	MSFLA	MSFLA > SFLA, GA, PSO	MSFLA > SFLA, GA, PSO	N/A	N/A	Economic load dispatch problem	Previous research work comparisons: $p = 100$, $m = 5$, $n = 20$, $s = N/A$, $N = 200$
70	Shayanfar et al. (2010a,b)	MSFLA	MSFLA > PSO	MSFLA > PSO	N/A	N/A	Unified power flow controllers in electrical power systems	Previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
71	Roy and Chakrabarti (2011)	MSFLA	MSFLA > GA	N/A	N/A	N/A	Economic load dispatch problem	Previous research work comparisons: $p = 100$; $m = 10$; $n = 10$; $s = 20$; $N = 10$
72	Malekpour and Niknam (2011)	MSFLA	MSFLA > PSO, SFLA	N/A	N/A	N/A	Volt/Var control at distribution networks	Previous research work comparisons: $p = 32$, $m = 4$, $n = 8$, $s = 10$, $N = 30$
73	Rahimi-Vahed and Mirzaei (2007)	HSFLA	HSFLA > MOGA	HSFLA > MOGA	N/A	HSFLA > MOGA	Flexible job/flow shop scheduling problem	SFLA-ETS (elite tabu search); MOGA: multi-objective GA; previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
74	Rahimi-Vahed and Mirzaei (2008)	HSFLA	HSFLA > MOGA	HSFLA > MOGA	HSFLA < MOGA	HSFLA > MOGA	Assembly line sequencing problem	SFLA-BO (bacteria optimization); previous research work comparisons: $p = 15$, $m = 5$, $n = 3$, $s = 30$, $N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
75	Rahimi-Vahed et al. (2008)	HSFLA	N/A	N/A	N/A	HSFLA > NSGA-II, SPEA-II	Flexible job/flow shop scheduling problem	SFLA-VNS (variable neighborhood search); previous research work comparisons: $p = 200$, $m = 4$, $n = 50$, $s = N/A$, $N = 500$
76	Li et al. (2008)	HSFLA	HSFLA > SFLA, DP	N/A	HSFLA > SFLA, DP	N/A	Mid-long term optimal operation of cascade hydropower stations	SFLA-CS (chaos search); benchmark comparisons: $p = 200$, $m = 20$, $n = 10$, $s = 100$, $N = 500$
77	Bhaduri and Bhaduri (2009)	HSFLA	N/A	HSFLA > SFLA, K-means algorithm	N/A	HSFLA > SFLA, K-means algorithm	Image segmentation for computer vision	SFLA-CSA (clonal selection algorithm); previous research work comparisons: $p = 25$, $m = 5$, $n = 5$, $s = 20$, $N = 100$
78	Niknam and Farsani (2010)	HSFLA	SFLA > PSO; HSFLA > SFLA	PSO > SFLA; HSFLA > PSO	SFLA > PSO; HSFLA > SFLA	HSFLA > SFLA, PSO	Feeder reconfiguration problem in distribution networks	MSFLA-SAPSO (self adaptive PSO); previous research work comparisons: $p = N/A$, $m = N/A$, $n = N/A$, $s = N/A$, $N = N/A$
79	Khorsandi et al. (2011)	HSFLA	HSFLA > SFLA, PSO, DE	HSFLA > SFLA, PSO, DE	N/A	N/A	Optimal reactive power dispatch problem	SFLA-NM (Nelder-Mead algorithm); DE = differential evolution; $p = 70$, $m = 5$, $n = 14$, $s = N/A$, $N = N/A$
80	Teekeng and Thammano (2011)	HSFLA	HSFLA > TS	N/A	N/A	N/A	Flexible job/flow shop scheduling problem	SFLA-FS (fuzzy system); benchmark comparisons; previous research work comparisons: $p = 50$, $m = 5$, $n = 10$, $s = N/A$, $N = 100$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
81	Niknam and Nayeripour (2011)	HSFLA	HSFLA > MPSO, SADPSO	HSFLA > MPSO, SADPSO	HSFLA > MPSO, SADPSO	HSFLA > MPSO, SADPSO	Feeder reconfiguration problem in distribution networks	MSFLA-SAMPPO (self-adaptive modified PSO); previous research work comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$
82	Pakraves and Shojaei (2011)	HSFLA	N/A	N/A	N/A	HSFLA > SFLA, PSO, GA	Optimization of stable points for poly vinyl acetate	SFLA-BO (bacterial optimization); SFLA-VPGA (variable population size GA); previous research work comparisons: $p = 60, m = 10, n = 6, s = N/A, N = N/A$
83	Seyedi et al. (2011)	HSFLA	N/A	HSFLA > GCPSO, PSO, GA	HSFLA > GCPSO, SPEA2	HSFLA > GCPSO, PSO, GA	VAr planning problem	SFLA-FL (fuzzy logic); previous research work comparisons: $p = 100, m = 10, n = 10, s = N/A, N = N/A$
84	Xu et al. (2011)	HSFLA	HSFLA > GA, DE	N/A	N/A	N/A	Hybrid flow-shop scheduling problem	SFLA-ML (meta-Lamarckian local search); DE = differential evolution; $p = 10, m = N/A, n = N/A, s = N/A, N = 10,000$
85	Li et al. (2011b)	HSFLA	HSFLA > SFLA	HSFLA > SFLA	N/A	HSFLA > SFLA	N/A	SFLA-PSO; benchmark comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$
86	Li et al. (2012a, b)	HSFLA	N/A	HSFLA > SFLA, PSO	HSFLA > SFLA, PSO	HSFLA > SFLA, PSO	Knapsack problem	MSFLA-EO (extremal optimization); benchmark comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$

Table 1 continued

No.	Reference	Proposed algorithm	Accuracy of the solution	Convergence rate	Less processing time	Generally performance	Application	Remarks ^a
87	Gritizadeh et al. (2012)	HSFLA	N/A	N/A	N/A	HSFLA > SFLA, PSO	Distribution expansion planning problem	SFLA-FL (fuzzy logic); previous research work comparisons: $p = N/A, m = N/A, n = N/A, s = N/A, N = N/A$
88	Zhang et al. (2012)	HSFLA	N/A	HSFLA > SFLA > AFS	N/A	HSFLA > SFLA, AFS	Power control problem in cognitive radio system	MSFLA-AF (artificial fish); previous research work comparisons: $p = 200, m = 20, n = 10, s = 30, N = 100$
89	Srinivasa Reddy and Vaisakh (2013)	HSFLA	HSFLA > GA, PSO, TS	N/A	HSFLA > GA, PSO, TS	N/A	Large scale non-convex economic dispatch problem	SFLA-DE (differential evolution); previous research work comparisons: $p = 200, m = 20, n = 10, s = 4, N = 300$

The operation “A > B” means A outperforms B and “A = B” means A and B has same performance. The best algorithm in each comparison is highlighted for the entries

^a Remarks the comparison type and also the parameters values considered in the researches (p = total number of frogs, m = the number of memplexes, n = the number of frogs in each memplex, s = the number of iteration for each memplex, and N = the maximum number of global iteration)

Based on the statistical result obtained from previous researches, evaluation phase in basic SFLA needs most modifications. For example, the worst frog's position never jumps over the best frog's position. This limitation decreases the convergence speed, causes premature convergence and reduces local search space in each memplex and convergence probability. In addition, the basic SFLA tries to balance between a deep and wide exploration of the search space that are close to a local optima (Xu et al. 2011). It is clear that if the worst and best frog's positions are close to each other, the change of leaping is also small. Thus, it causes to being trapped in the local optimum, and premature convergence reported by several researchers such as Elbeltagi et al. (2007) is a concern in basic SFLA.

In this section, MSFLA proposed by previous researchers are considered separately. Also, the goal of the modifications and their compensation are highlighted. Additionally, the results of comparisons between the proposed MSFLA with other evolutionary algorithms on different features are located in Table 1.

The researchers, Teekeng and Thammano (2011) have considered one more step into their proposed MSFLA. By this step, for each memplex, a number of frogs (usually with higher fitness values) are chosen to make a sub-memplex which performs the local exploration independently. Sub-memplex could improve the convergence rate and processing times.

To overcome to premature convergence in SFLA, Elbeltagi et al. (2007) and Xu et al. (2011) proposed a new equation by applying a new factor named 'search-acceleration'. The factor as a positive constant value, linear, or nonlinear function of time, could balance local and global local exploration by considering the global exploration fundamentals and search extremely in the region of feasible solutions.

Zhijin et al. (2008) modify SFLA to solve discrete problems. Therefore, a threshold selection strategy was employed in frog leaping operation in solving multi-user detection problems.

To defeat the problems of premature convergence, low convergence speed, and finally to improve optimization accuracy in MSFLA, Zhen et al. (2009) employed two important modifications of SFLA: using a new division strategy of memplexes benefits the internal learning effect to make the memplex's performance uniform; canceling the construction of sub-memplex to give the better frogs more learning chances and increase global exploration.

To overcome the limitations of basic SFLA in the evolution phase and improving the memetic evolution process, it was recommended by Li and Wang (2011) to utilize local and global best information for frog leaping and transfer them between individual frogs.

Consequently, Li et al. (2010) applied an MSFLA to solve multi-objective optimization problems. The offered algo-

rithm applied a self-adaptive niche technique (a storing technique) to handle nondominated solutions. As well, Li et al. (2010) applied the sort strategy proposed by Rahimi-Vahed and Mirzaei (2008) and Rahimi-Vahed et al. (2008) to handle multi-objective problems. According to the computational results, the presented MSFLA is more efficient and competitive for solving the complex problems compared with dynamic programming and NSGA-II.

Also, Li and Wang (2011) extended basic SFLA by employing an encoding based on urban-based sequence and applied a new strategy for individuals to deal with combinatorial optimization problems such as traveling salesman. Experimental results indicated the effectiveness, maintaining diversity, achieving convergence and time cost of the proposed MSFLA compared with some other evolutionary techniques (see Table 1).

To increase the optimization accuracy with minimum iteration number, Roy (2011) proposed a MSFLA by using GA crossover operation in local and global search. This MSFLA was applied to solve minimum spanning tree problems.

Shayanfar et al. (2010a,b) utilized a MSFLA to enhance local search. The MSFLA presented in that paper applied a new equation for updating the worst frog's position.

Compared to multi-objective optimization problems, Malekpour et al. (2012), Niknam et al. (2011a, 2012) and developed a new MSFLA to handle multi-objective problems. The proposed MSFLA applied a fuzzy clustering technique to handle and normalize various objective functions. Thus, the objective functions were formulated as fuzzy sets. Also, to improve SFLA stability and search ability for finding the global optima, Malekpour et al. (2012) and Niknam et al. (2011c) proposed a new solution to find the position of the selected frog. They applied a chaotic local search (CLS) to create a new solution if the quality of the new frogs was not improved compared to the worst frog. Based on the evaluation result, the proposed algorithm is exact and can be used in various applications. Niknam et al. (2011c) solved the economic load dispatch problem by the proposed MSFLA.

Additionally, Niknam et al. (2011b) modified the basic SFLA to enhance the convergence rate to solve multi-objective optimization problems. In the presented MSFLA, an external repository is defined to hold nondominated solutions. Also, a fuzzy clustering method is applied to manage the repository's size. Evaluation results illustrated that MSFLA was more effective than GA and PSO algorithms.

Furthermore, Niknam et al. (2011a) employed a new mutation for reducing computational time, raising solutions' quality, as well as avoiding being trapped in the local optima.

Moreover, Niknam et al. (2012) used a novel MSFLA by modifying frog leaping rule in SFLA and Tribe-MSFLA was employed to prevent the prematurity. Each memplex is considered as a tribe in Tribe-MSFLA.

To improve the global searching capability of SFLA, [Pu et al. \(2011\)](#) employed a new MSFLA. The algorithm was proposed by modifying the division method of SFLA to balance the performance of memplexes, and by using a new frog leaping rule and to give more chance for the best frog to be evolved. The results in that paper showed that the MSFLA is better than the basic SFLA and PSO algorithm.

To enhance the quality of the initial population, local intensification capability and search efficiency, [Pan et al. \(2010\)](#) presented a new MSFLA. The proposed algorithm used an effective heuristic to generate an initial population with a definite level of diversity and quality. In addition, the MSFLA employs a simple effective local search to develop the local intensification capability. Also, a high-speed technique was presented to advance the search efficiency.

To enhance the effectiveness of basic SFLA, [Chittineni et al. \(2011a, b\)](#) applied a new MSFLA by employing the local best value of each memplex rather than creating a new frog.

To initialize a population with high quality, search exploitation and the exploitation capability, [Li et al. \(2012a, b\)](#) developed an MSFLA. The following modifications were done in the MSFLA: first, population initialization (by using 3 initial rules); second, evolution process in each memplex (by using two new crossover techniques to create a new solution); third, local search (using several neighborhood structures by considering the problem constraints or the problem objectives to improve the search exploitation and exploration capability of the algorithm). There is a large variety of published algorithms which were compared with the proposed MSFLA such as hybrid PSO-SA, GA, hybrid PSO-tabu search, artificial immune algorithm (AIA), the multi-objective genetic algorithm (MOGA) and the knowledge-based ACO (KBACO). The experimental results in that paper indicated the effectiveness of the proposed algorithm.

An effective MSFLA was proposed by [Wang et al. \(2011\)](#) to improve the capability of exploitation, to solve multi-mode resource-constraint project scheduling problems. Population in the proposed algorithm was generated by multi-mode forward-backward improvement as well as a simplified two-point crossover using traditional binary encoded GA. Simulation results illustrated that the presented MSFLA was effective in improving the performance compared with PSO.

In addition, [Wang et al. \(2011\)](#) presented a novel MSFLA to handle flow shop scheduling problems. The developed algorithm applies insert-neighborhood-based local search to improve the search capability. Also, it adopted roulette wheel selection to find the global best frog in the early stage of evolution to expand the search space. The statistical results found by the MSFLA are significantly better than those by the SFLA and PSO algorithms.

[Chen et al. \(2011a, b\)](#) proposed a new local search based on random keys scheme in MSFLA to increase the conver-

gence and accuracy in the optimization of job-shop scheduling problem. In addition, [Chen et al. \(2011a\)](#) improved SFLA in solving component sequencing problem by using mutation operation as well as applying a modified NNH algorithm in generating initial solutions. This algorithm could dominate randomness in increasing the stability of the initial solutions.

[Kimiyağhalam \(2012\)](#) applied mutation operation of GA to avoid being trapped into the local optimal by searching new positions outside of local optimal position. The close distance between the best and worst positions in each memplex may decrease the chance of jumping to the best point in the memplex.

[Jafari et al. \(2012\)](#) developed a new MSFLA for automated sizing of analog integrated circuits. In that paper, an equation for frog leaping was considered to enhance the local search ability. Also, mutation was applied to create new frogs instead of random selection to enhance the convergence speed. The authors proved that the proposed MSFLA outperforms GA and imperialist competitive algorithm in terms of processing time and performance.

Moreover, [Huynh \(2008\)](#) modified the frog leaping equation in basic SFLA to develop a MSFLA for optimization of multi-variable controllers. Based on the results obtained from that paper, the proposed MSFLA outperforms GA in terms of convergence speed and performance. [Li et al. \(2012a\)](#) and [Wang and Di \(2010\)](#) also presented an MSFLA by extending the frog leaping formula to avoid the premature convergence for solving knapsack problem and image segmentation problem, respectively.

[Liu et al. \(2012\)](#) proposed an MSFLA based on multi-objective dynamic population shuffled frog leaping biclustering algorithm. The next generation in the presented algorithm is dynamically adjusted according to dynamic population strategy which increases the search ability. According to the result, the presented algorithm outperforms SFLA, PSO and dynamic PSO (DPSO) algorithms in terms of diversity and convergence speed.

[Huynh and Nguyen \(2009\)](#), [Shayanfar et al. \(2010a, b\)](#) and [Sayedi et al. \(2012\)](#) applied a frog leaping rule for local search and a mimetic shuffling rule for sharing global information to enhance searching abilities and avoid being trapped into the local optimal. Thus, researchers applied a new equation to decrease the maximum uncertainties exponentially. This technique has been used to optimize fuzzy controllers, unified power flow controllers, and economic dispatch problem.

[Lin et al. \(2011\)](#) modified SFLA by using inertia weight in the algorithm which is decreased linearly from 0.9 to 0.4 during the execution. This weight could make a balance between exploration and exploitation. Also, [Lin et al. \(2012\)](#) showed that finding x_g after finishing the local search in each memplex will decrease the convergence rate in basic SFLA. Thus,

modified SFLA was proposed by finding x_g after updating each memplex.

Sardou et al. (2012) applied two modifications on SFLA to optimize the distribution automation system by using (1) fuzzy membership functions for solving multi-objective problems and (2) considering a subset of memplexes to increase a local search area and avoid being trapped into the local optima.

Also, a new modification is considered by Malekpour and Niknam (2011) to improve the local search ability in SFLA. In the proposed MSFLA, four solutions are chosen randomly among the list of sorted solutions to be changed simultaneously.

5 Hybrid SFLA

As mentioned in the previous sections, an optimization algorithm can be enhanced by using the advantages of other algorithms. These types of algorithms are known as hybrid algorithms. The main goal of hybridization is advancing the effectiveness of individual basic algorithms, expanding the search space, enhancing convergence, and improving local exploration. Also, it could design flexible, coherent, and effective algorithms to handle continuous or multi-objective optimization problems.

In recent years, different structures for HSFLA have been developed by previous researchers. This section highlights the proposed hybrid algorithms by focusing on their particular advantages. Additionally, the results of comparisons between the proposed HSFL with other evolutionary algorithms on different features are located in Table 1.

To solve global optimization problems, Zhen et al. (2007) proposed a new HSFLA by applying an effective adaptive learning strategy in PSO. As high computational cost is a disadvantage of the basic SFLA, the self-learning ability in memplexes will find the best local solutions fast. Therefore, the algorithm increases convergence speed and escapes the local optima. According to the comparison results, the proposed hybrid algorithm outperforms PSO and SFLA in terms of convergence speed, being away from the local minima, and computational time for searching solutions.

To enhance convergence and quality of the shuffled frogs in basic SFLA, Rahimi-Vahed and Mirzaei (2007) introduced a new HSFLA to solve bi-criteria permutation flow shop scheduling problem. They applied a novel elite tabu search (ETS) algorithm for generating high-quality solutions. Also, they used a strategy to revise the dynamic ideal point (DIP) and employed an adaptive pareto archive set to utilize new nondominated solutions when pareto archive size goes to the upper limit.

Furthermore, the same authors in Rahimi-Vahed and Mirzaei (2008) developed a hybrid optimization algorithm based on SFLA and bacteria optimization to handle a mixed-

model assembly line sequencing problem. BO includes two operations: bacterial mutation and gene transfer. Mutation was used to optimize the chromosome of a single bacterium. As well, transferring the genes could shift the information between the bacteria in the population. Consequently, Rahimi-Vahed et al. (2008) integrated basic SFLA and variable neighborhood search (VNS) to search pareto optimal solutions. Additionally, Rahimi-Vahed and Mirzaei (2008) and Rahimi-Vahed et al. (2008) applied a multi-start elite tabu search algorithm to construct initial diverse high-quality frogs. According to the computational results calculated by Rahimi-Vahed and Mirzaei (2008) and Rahimi-Vahed et al. (2008), the proposed HSFLA outperforms the well-known algorithms (SPEA-II and NSGA-II), significantly in large-sized problems. In addition, the developed algorithm needs more computational time compared to GA, but it is reasonable by considering the quality of the result solutions.

To being trapped into local optima and increase diversity of solution, Li et al. (2008) proposed a HSFLA based on Chaos search. Chaos algorithm could improve x_g which discontinues evolution by generating new optimal solutions.

To enhance the convergence rate, accuracy, and solution stability in basic SFLA in solving image segmentation problems, Bhaduri and Bhaduri (2009), Chittineni et al. (2011a,b) and Li et al. (2011a) applied clonal selection algorithm (CSA) to SFLA. CSA which is inspired from immune mechanism of human body is able to replace most horrible antibodies in the population with new random ones. Therefore, SFLA processes the worst subset of population and CSA processes the best subset of population. The computational results showed that the proposed HSFLA outperforms *K*-means algorithm, CLONALG and basic SFLA.

Khorsandi et al. (2011) applied a new local search based on Nelder–Mead (NM) algorithm to basic SFLA in solving a nonlinear mixed-variable optimization problem. In the proposed HSFLA, the researchers attempted to improve the local search ability by replacing the worst solution in the population with a new one which is better than the current solution. As well, meta-Lamarckian local search which is applied by Xu et al. (2011) is a good way to improve the search ability in basic SFLA.

Zhang et al. (2012) utilized a HSFLA by using the basic ideas of artificial fish to enhance the accuracy of the solution. The experimental results indicated that the new HSFLA improves global convergence and escapes local optima. Moreover, according to the evaluation results, the proposed HSFLA could enhance system performance and controllability on the target and also reduce the user transmission power.

To enhance local exploration and performance of SFLA, and avoid premature convergence for solving the distribution feeder reconfiguration problem, Niknam and Farsani (2010) developed a new HSFLA. The proposed algorithm

named SAPSP–MSFLA uses self-adaptive PSO (using two new turning parameters and increase of other variables' dimensions) and MSFLA (using new frog leaping equation to expand the length and trend of each frog's jump). The results showed that the proposed HSFLA is very powerful for global optimization. In addition, Niknam et al. (2011a, b) extended an HSFLA that combines self-adaptive modified PSO (SAMPPO) with the MSFLA to proceed toward the global solution and increase accurate convergence. Low convergence speed and premature convergence are two disadvantages in basic SFLA. On the other hand, MPSO algorithm (using a new mutation technique) is a robust global search procedure, but has some limitations on computational time and accuracy. As a result, the combination of MSFLA and SAMPPO algorithms called SAMPPO–MSFLA has high convergence rate and more accuracy than SAMPPO and MSFLA individually. To solve N -dimensional problems through the hybrid algorithms presented by Niknam and Farsani (2010) and Niknam et al. (2011b), the population size was considered as $3N$. The top N particles are improved by MSFLA, and the other $2N$ particles are adjusted through SAPSO or SAMPPO algorithms.

To improve the effectiveness of SFLA and frog selection for sub-memplex in solving flexible job-shop scheduling problem, Teekeng and Thammano (2011) proposed a new HSFLA based on fuzzy system (SFLA–FS). The new algorithm applied fuzzy roulette wheel selection to assign frogs into sub-memplexes. Experimental results showed that the applied operation outperformed usual rank selection. Additionally, a local search was utilized to enhance the accuracy of the solution.

To enhance success rate and speed, Baghmisheh et al. (2011) presented a new HSFLA to handle various optimization problems. In the proposed algorithm, a discrete version of SFLA with a difference in worst frog leaping process in each memplex was applied. The process applied DPSO algorithm as well as mutation and crossover operators of binary GA (BGA). Evaluation results for computational time showed that the proposed HSFLA is slower than basic SFLA while it outperforms DPSO and GA. In addition, HSFLA is better than basic SFLA, BGA, and DPSO in terms of both speed and success rate.

To improve the performance of SFLA, Pakraves and Shojaei (2011) presented two effective HSFLAs based on variable population size GA (FSFLA–VPGA) and bacterial optimization (FSFLA–BO) algorithm. After the completion of the main SFLA loop, VPGA or BO was called to enhance new produced solutions. After a certain number of iterations, the enhanced solutions were returned to the SFLA. High abilities of VPGA and BO algorithms in finding the global optima make basic SFLA more effective in optimization.

In addition, Seyedi et al. (2011) developed an HSFLA by applying fuzzy logic to achieve a set of fuzzy objectives to

solve multi-objective planning problems. Based on the computational result, the HSFLA outperforms PSO, guaranteed convergence PSO (GCPSO) and GA. Also, Gitizadeh et al. (2012) integrated fuzzy approach to solve multi-objective distribution network expansion planning.

Moreover, Li et al. (2012b) presented an HSFLA by modifying the frog leaping rule and employing a hill climbing local search called extremal optimization (EO). EO has a high local search capability and could improve the effectiveness of basic SFLA in optimization.

Srinivasa Reddy and Vaisakh (2013) employed differential evolution algorithm in HSFLA. In the proposed hybrid algorithm, all the solutions in each memplex could take part in the evolution. As well, using memetic evolution process in differential evolution algorithm and also a novel mutation could enhance the local and global search ability, respectively.

6 Highlights on SFLA

SFLA is a robust algorithm with local and global search abilities to solve various large-scale and complex optimization problems. This algorithm integrates the advantages of MA and PSO algorithms. SFLA uses memetic evolution in local search and then PSO approach is applied to complete the search. Shuffling strategy could transfer information between local and global explorations.

6.1 Applications

According to the statistical result found from previous researches (see Table 1) and as it is clear from Table 2, SFLA has been functional in different sorts of optimization problems and is practical for various applications. Table 2 shows the main types of applications which have used SFLA and Fig. 2 indicates the percentage of usage of SFLA in solving the problems considered by a number of researchers. From Fig. 2, it is clear that SFLA has been mostly employed for flexible job/flow shop scheduling problems, electrical power flow optimization problems and classification problems. The optimization results on different applications show that SFLA is effective in various optimization problems, especially in solving large-scale combination optimization problems, high-dimensional problems and when high accurate solutions are required.

6.2 Control parameters

The control parameters in SFLA have to be initialized for optimization. These parameters are the total number of frogs or population size (p), number of memplexes (m), number of frogs in each memplex (n), maximum number of

Table 2 Different application types have applied SFLA by previous researchers

No.	Application type
1	Flexible job/flow shop scheduling problem
2	Feeder reconfiguration problem in distribution networks
3	Water distribution network optimization problems
4	Detection of fault location in distribution networks
5	Electrical power flow optimization
6	Continuous optimization problem
7	Finance-based/project scheduling problem
8	Traveling salesman problem
9	Volt/Var control problem in distribution systems
10	Classification problems
11	Knapsack problem
12	Distribution expansion planning problem
13	Optimization of stable points for poly vinyl acetate
14	Optimization of UAV flight controller
15	Sequencing problem
16	Economic load dispatch optimization problem
17	Flood control problem
18	Multi-user detection problem–telecommunication
19	Optimization of parameters of induction machines
20	Optimization of placement in distribution network
21	Networked two-layer learning control systems
22	Optimization of fuzzy controller
23	RNA secondary structure prediction
24	Production planning problem
25	Power system stabilizer
26	Viewpoint selection in visualization of 3D datasets
27	Mid- to long-term optimal operation of cascade hydropower stations
28	Optimization of ANN model for prediction of power system load
29	Optimization of analog integrated circuits sizing
30	Discrete/real-valued optimization problems
31	Unit commitment scheduling problem

evolution or iteration (N), and maximum number of iteration per memplex (s). Although the values of parameters vary in different problems, reviewing the values considered by previous researchers and optimization results obtained by them show that determination of proper number of frogs is an important issue in optimization. Increasing the number of frogs could enhance the accuracy while it could also increase the processing time. Specification of the proper number of memplexes in SFLA is a major difference between the power of SFLA with PSO and GA. As well, after reviewing the number of memplexes considered by different papers, it was observed that the number of memplexes was usually considered as 10 % of the number of frogs. As well, the num-

ber of frogs per memplex was determined by (p/m). Moreover, increasing the iteration number in memplexes could increase the accuracy of the result, although the processing time would be increased. In previous works, this iteration has been defined as a number between $m/2$ and $m \times 2$. The number of global iterations completely depends on the application, the expected precision of the solutions and usually considered between 100 and 1,000.

6.3 Comparable algorithms

The most evolutionary algorithms which have been compared with SFLA by previous researchers are GA, PSO, ABC, SA, MA, and ACO. Also, some related hybrid algorithms such as SAMPSO, SPSO, dominated sorted genetic algorithm (NSGA), AIA, KBACO, multi-objective genetic algorithm (MOGA), multi-objective particle swarm optimization (MOPSO), and strength pareto evolutionary algorithm (SPEA) are considered for evaluation. As it is clear from Table 1, the most comparisons are between SFLA and PSO, or SFLA and GA. Additionally, although a few number of researchers such as Rao (2011) reported ABC as a robust optimization algorithm, there is not enough evidence to prove that SFLA could outperform ABC in special applications. According to the statistical result obtained from previous studies (highlighted in Table 1), around 34 % of the studies are on basic SFLA. However, MSFLA and HSFLA could overcome basic SFLA to enhance the SFLA performance for solving complex, multi-objective, and continuous optimization problems.

6.4 Consideration features

The accuracy of the solution, convergence rate, processing time, and performance are the key features of SFLA considered by the most number of researchers to be evaluated with other evolutionary optimization algorithms. Based on the comparison result listed in Table 1, SFLA outperforms the others especially in terms of convergence rate as well as performance. Also, based on a few number of evaluation results, although convergence rate in PSO is equal or sometimes more than the rate in basic SFLA (Eusuff et al. 2006; Niknam and Farsani 2010), a modified or hybrid SFLA could overcome this shortcoming.

7 Highlights on improvements of SFLA

In the population-based meta-heuristic optimization algorithm, premature convergence may happen for various reasons: population is converged to local optima of objective functions; diversity of the population is lost; the search process is slow; search has not proceeded at all. There are

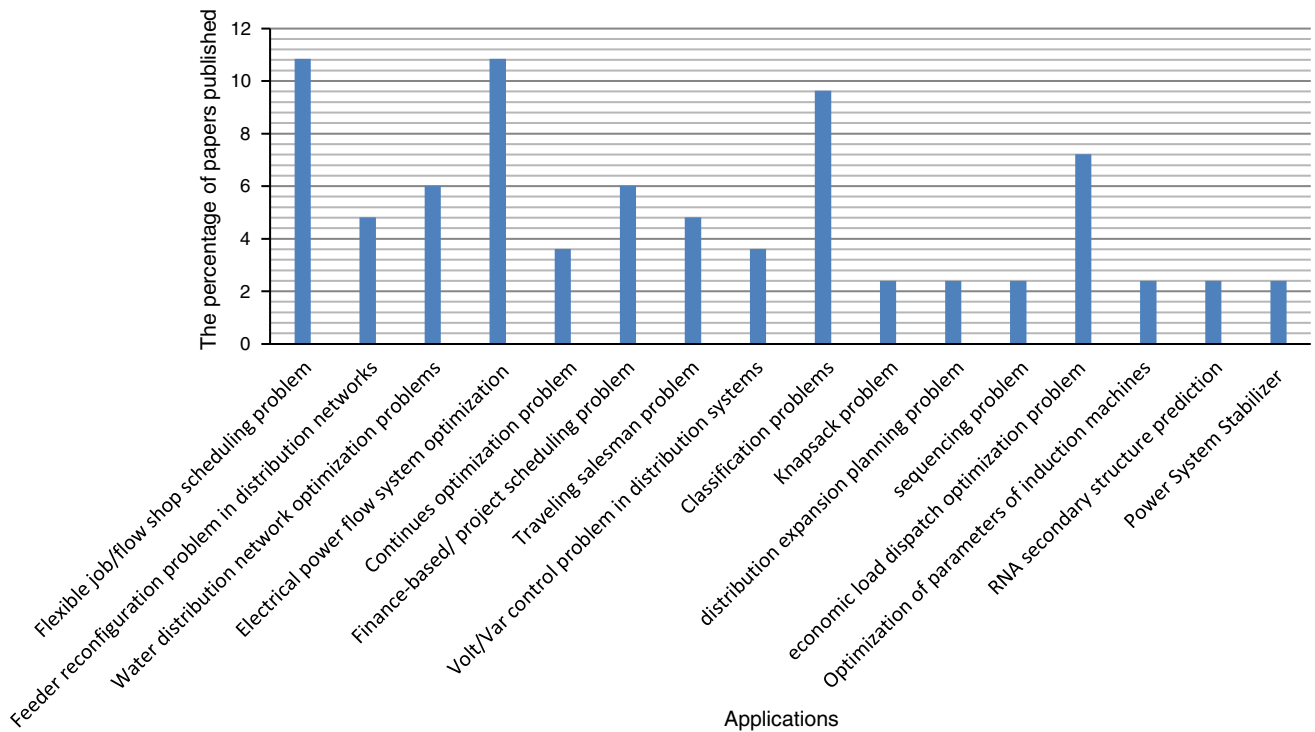


Fig. 2 The percentages of papers which applied SFLA in different application types

several strategies that can moderate these shortages. This section focuses on the most important enhancement performed on the basic SFLA by previous researchers. The highlighted enhancements are obtained from the statistical results and evaluations of the researches (see Table 1) and are based on the most common and effective modifications considered by a large number of studies. According to the result found from the previous researches, around 85 % of the papers published in relation to MSFLA or HSFLA have tried to propose or enhance the local search by introducing new frog leaping rule.

7.1 To handle multi-objective optimization problems

According to the results reported by Niknam et al. (2011a, b, 2012), Malekpour et al. (2012), Seyedi et al. (2011), Giti-zadeh et al. (2012), and Sardou et al. (2012) as the objective functions are indefinite, a clustering procedure using fuzzy set could be applied to organize the repository’s size to distinguish the best compromise solution using the fuzzy membership function. The membership function of objective functions for each individual in the repository is considered as follows:

$$\mu_{f_i}(X) = \begin{cases} 1 & \text{for } f_i(X) \leq f_i^{\min} \\ 0 & \text{for } f_i(X) \geq f_i^{\max} \\ \frac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \leq f_i(X) \leq f_i^{\max} \end{cases}, \quad (6)$$

where f_i^{\max} and f_i^{\min} indicate the maximum and minimum values of the functions, respectively. The membership value of individuals in the repository is calculated by the following equation:

$$N_{\mu}(j) = \frac{\sum_{k=1}^n w_k \times \mu_{fk}(X_j)}{\sum_{j=1}^m \sum_{k=1}^n w_k \times \mu_{fk}(X_j)}, \quad (7)$$

where m, n are the number of solutions and objective functions, respectively, and w_k is the weight of the k th objective function. $N_{\mu}(j)$ as a normalized value shows a type of decision-making criterion.

7.2 To avoid being trapped into local optima/to enhance the local exploration

Based on the results presented by previous researches, two operations, mutation of the frogs and division of the frogs into memplexes, are powerful strategies which can maintain the diversity of the population and extend the exploration area. According to previous works, proposing new mutations which could cause convergence of the global optima and avoid being trapped into the local optima are the important modifications. The victorious modifications are motivated from the theory noted by most of the researchers that SFLA needs a wide local search space at former iterations to avoid premature convergence and a narrow search space to speed up convergence rate at the next iterations.

- One strategy for modifying the mutation in basic SFLA is considering a new factor in Eq. (4) (Elbeltagi et al. 2007; Wang and Di 2010; Xu et al. 2011). This constant factor presents the searching scale for frog leaping step and should be assigned to a large value. Thus, the new frog leaping equation is as follows:

$$x'_i = x_i + r \times c \times (x_b - x_w), \quad (8)$$

where r indicates a random number between $0 < r < c$ while $1 < c < 2$.

- Additionally, employing one more factor in Eq. (8) as an inertia weight could regulate the search operation and enhance local exploration. This factor is assigned to a large value at first (at the initializing phase) and is reduced regularly to find more sophisticated solutions (Li et al. 2012a; Huynh (2008); Jafari et al. 2012). The new frog leaping formula is as follows:

$$x'_i = x_i + w + r \times c \times (x_b - x_w), \quad (9)$$

where r indicates a random number between -1 and 1 , also $w_{\min} < w < w_{\max}$, in which w_{\min} and w_{\max} define the minimum and maximum permitted perception, respectively. This perception weight is linearly decreased during the algorithm run.

- As well, based on the theory of search space noted by Huynh and Nguyen (2009), Sayedi et al. (2012), and Shayanfar et al. (2010a, b), Eq. (10) has been proposed for finding the perception weight in i th dimension of the search space. Using a decay factor λ to decrease the perception weight exponentially is an effective way to enhance the local exploration ability.

$$w_i = \lambda_i w_0, \quad (10)$$

where λ_i indicates a random number between 0 and 1 , and also w_0 is the initial weight.

- Furthermore, considering a frog's position with higher fitness value instead of the worst one in Eq. (4) could improve the diversity. In this way, the mean value of individual in each memplex could also be replaced with the worst one (Shayanfar et al. 2010a, b; Malekpour et al. 2012).
- In addition, mutation could apply a new random frog in Eq. (4) to calculate a trial mutated vector (Niknam et al. 2011a; Perez et al. 2012; Chen et al. 2011a; Gomez-Gonzalez 2012). Thus, the following equation could be useful to find the new position,

$$x'_i = X_{\text{rand}} + r \times (X_b - X_{\text{rand}}) + r \times (X_g - X_{\text{rand}}), \quad (11)$$

where x_{rand} is a randomly generated vector.

- Also, a new algorithm named CLS could be utilized to search the best frogs for each memplex and initial population. Hence after improving the solutions, the best solution is replaced with the worst frog in Eq. (4) (Malekpour et al. 2012; Niknam et al. 2011c).
- As well, considering more frogs among the sorted frogs fed into Eq. (4) could enhance the convergence speed (Niknam et al. 2011c, 2012) and diversity of the frogs.
- On the other hand, applying a new division method to make the memplexes' performance uniform could help to enhance the internal learning process in each memplex (Zhen et al. 2009). In this kind of division, the frog with the highest fitness value moves to the first memplex that with the second highest value moves to m th memplex. The frog with the third value moves to the first memplex again. This steps continues until the last frog is placed in the proper memplex.
- Hybridization of clonal selection algorithm and SFLA suggested by Bhaduri and Bhaduri (2009) and Chittineni et al. (2011a, b) improves the convergence rate and helps avoid being trapped into the local minima.

7.3 To enhance global exploration/quality of shuffled frogs

Using a wide search space and considering more frogs in the evaluation could be good ways to enhance global search ability in SFLA. On the other hand, higher quality of shuffled frogs could expand local and global exploration, raise convergence probability, and avoid premature convergence. Based on the result obtained from previous researches, the following strategies could help to enhance the quality of shuffled frogs and convergence probability.

- The frogs in the population get updated information from the local and the global best solutions, and the search is infected by the global best solution. Consequently, we use insert neighborhood-based local searches for finding local and global best frogs and using roulette wheel selection for selecting the best frog. Roulette wheel selection can exploit the frogs with better memes (value) for development of new ideas, which ensure the fast convergence (Wang et al. 2011).
- Applying the strategy of self-adaptive PSO as a local exploration and integrating the information from local searches in parallel could increase the accuracy and convergence rate (Niknam et al. 2011a, b).
- By integrating the two operations of bacterial optimization algorithm, bacterial mutation and gene transfer, SFLA reaches higher convergence and better performance. These operations could optimize the frog in a population and transfer the information between the frogs in the population (Rahimi-Vahed and Mirzaei 2008).

- Variable neighborhood descent could be utilized to raise the diversification and frogs' quality in memplexes individually (Rahimi-Vahed et al. 2008; Pakravesh and Shojaei 2011).
- Employing the concept of AFSA into SFLA during global information exchange and local deep search could enhance the convergent rate and local and global exploration as well as accuracy (Zhang et al. 2012). This strategy modifies the mutation operation in finding the new frog's position or random frog's position.
- Although using sub-memplex recommended by some researchers enhance local exploration, it could not improve global exploration. Zhen et al. (2009) ignored the construction of sub-memplex and combined local and global exploration space to expand evaluation space in each memplex. This modification increased the learning ability of good frogs to avoid being trapped into the local optima and increase the solutions' diversity.
- Hybridization of clonal selection algorithm and SFLA suggested by Bhaduri and Bhaduri (2009) and Chittineni et al. (2011a, b) could increase the social behavior of the new algorithm and increase global exploration with a high convergence rate.

7.4 Processing time

Modifying the process of leaping frog's position in each memplex could reduce the processing time of the optimization. This modification includes the following operations: using the Eq. (4) to calculate the new frog's position, using a mutation operator of GA to improve the result, using crossover operator of GA between the worst and best global frog, or finally finding the frog's new position randomly (Baghmisheh et al. 2011; Roy 2011).

7.5 Enhancing the quality of the initial population

SFLA usually begins with an initial collection of solutions (frogs) constructed randomly. Thus, the result (optimal solution) of the algorithm strongly depends on the initial set. Based on the result reached by previous researches, the following highlights are obtained.

- Using a heuristic or initialization rules to distinguish better situation for a solution could initialize a population with high quality and high diversification. It produces an individual or frog, while all other solutions are produced accidentally to improve the population's diversity (Pan et al. 2010; Li et al. 2012a, b).
- The statistical results presented by Rahimi-Vahed and Mirzaei (2007, 2008), and Rahimi-Vahed et al. (2008) show that ETS meta-heuristic algorithm could generate a set of solutions (frogs) with high quality. This search

begins from a predefined point called ideal point which is a virtual point considered by the optimization of each objective function separately and could be estimated by the DIP. The main advantage of tabu search is sharing the frequency-based memory to look for less visited spaces. Thus, solution space could be searched in various directions to obtain high diversification.

8 Conclusion

In this study, the previous researches related to SFLA for solving optimization in various applications are considered. The structure of basic SFLA and its next generations are considered separately. Also, the advantages of the next generations of SFLA are reviewed. These advantages are specified based on some key features of the algorithm. The statistical results obtained from the applications indicate that SFLA is widely applied for flexible job shop scheduling problems. The experimental results in terms of performance show that SFLA outperforms other evolutionary algorithms such as GA, PSO, ACO, ABC, and SA and some of their next generations.

Based on the experimental result, the performance of the SFLA is significantly enhanced by utilizing novel modification or hybridization. Nowadays, a wide range of researchers have proposed MSFLA and HSFLA on various problems. In addition, based on the literature review and as HSFL could bring the best out of basic SFLA and other evolutionary algorithms, HSFL could outperform the other algorithms in solving complex and continuous problem.

Moreover, the proposed SFLAs by previous researchers were evaluated to find their most common and valuable improvements. It is clear that there has not been enough effort to enhance the processing time and the accuracy of the result.

In summary, the SFLA is a comprehensive meta-heuristic optimization algorithm and could be extended to various optimization problems. Therefore, the results of this research can be acquired for prospective researches to be applied to different processes or to improve old studies by considering the advantages of other systems proposed by previous researchers.

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References

- Alghazi A, Selim S, Elazouni A (2012) Performance of shuffled frog-leaping algorithm in finance-based scheduling. *J Comput Civ Eng* (JUNE) 26(3):396–408

- Amiri B, Fathian M, Maroosi A (2009) Application of shuffled frog-leaping algorithm on clustering. *Int J Adv Manuf Technol* 45(1–2):199–209
- Anita J, Raglend IJ (2012) Solution of unit commitment problem using shuffled frog leaping algorithm. In: *Proceedings of the international conference on computing, electronics and electrical technologies*, pp 109–115
- Baghmisheh MT, Madani K, Navarraf A (2011) A discrete shuffled frog optimization algorithm. *Artif Intell Rev* 36(4):267–284
- Banati H, Mehta S (2012) SEVO?: bio-inspired analytical tool for unimodal and multimodal optimization. In: *Proceedings of the international conference*, pp 557–566
- Bhaduri A, Bhaduri A (2009) Color image segmentation using clonal selection-based shuffled frog leaping algorithm. In: *Proceedings of the international conference on advances in recent technologies in communication and computing*, pp 517–520
- Chen G (2009) Combined economic emission dispatch using SFLA. In: *Proceedings of the international conference on information engineering and computer science*, pp 1–4
- Chen G, Chen J, Duan X (2009) Power flow and dynamic optimal power flow including wind farms. In: *Proceedings of the international conference on sustainable power generation and supply*, pp 1–6
- Chen MR, Li X et al (2011a) An improved shuffled frog-leaping algorithm for job-shop scheduling problem. In: *Proceedings of the second international conference on innovations in bio-inspired computing and applications*, pp 203–206
- Chen T, Luo J, Hu Y (2011b) Component placement process optimization for multi-head surface mounting machine based on tabu search and improved shuffled frog-leaping algorithm. In: *Proceedings of the 3rd international workshop on intelligent systems and applications*, pp 1–4
- Chittineni S, Pradeep A, Dinesh G (2011a) A parallel hybridization of clonal selection with shuffled frog leaping algorithm for solving global optimization problems (P-AISFLA). In: *Proceedings of the second international conference on swarm, evolutionary and memetic computing*, vol 2, pp 211–222
- Chittineni S, Godavarthi D, Pradeep ANS (2011b) A modified and efficient shuffled frog leaping algorithm (MSFLA) for unsupervised data clustering. In: *Proceedings of the advances in computing and communications*, pp 543–551
- Dorigo M (1992) *Optimization, Learning and Natural Algorithms* (in Italian). Ph.D. thesis, Dipartimento di Elettronica, Politecnico di Milano, Italy
- Duan JH, Pan Q (2010) Scheduling the lot-streaming flow shop problem using a shuffled frog-leaping algorithm. In: *Proceedings of the sixth international conference on natural computation (Icnc)*, pp 4263–4266
- Eberhart RC, Kennedy J (1995) A new optimizer using particle swarm theory. In: *Proceedings of the sixth international symposium on micro machine and human science*, vol 1, IEEE Press, Nagoya, pp 39–43
- Eghbal M, Saha T, Hasan K (2011) Transmission expansion planning by meta-heuristic techniques: a comparison of shuffled frog leaping algorithm, PSO and GA. *Power and Energy Society General Meeting, IEEE*, pp 1–8
- Elbeltagi E, Hegazy T, Grierson D (2007) A modified shuffled frog-leaping optimization algorithm: applications to project management. *Struct Infrastruct Eng* 3(1):53–60
- Eusuff MM, Lansey KE (2003) Optimization of water distribution network design using the shuffled frog leaping algorithm. *J Water Resour Plan Manag* 129(3):210–225
- Eusuff MM (2004) Water resources decision making using meta-heuristic optimization methods. Ph.D. thesis, University of Arizona
- Eusuff MM, Lansey K, Pasha F (2006) Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. *Eng Optim* 38(2):129–154
- Fang C, Wang L (2012) An effective shuffled frog-leaping algorithm for resource-constrained project scheduling problem. *Comput Oper Res* 39(5):890–901
- Gitizadeh M, Vahed AA, Aghaei J (2012) Multistage distribution system expansion planning considering distributed generation using hybrid evolutionary algorithms. *Appl Energy* 101:655–666
- Gomez-Gonzalez M (2012) Shuffled frog-leaping algorithm for parameter estimation of a double-cage asynchronous machine. *Power Appl IET* 6(8):484–490
- Gomez-Gonzalez M, Ruiz-Rodriguez FJ, Jurado F (2013) A binary SFLA for probabilistic three-phase load flow in unbalanced distribution systems with technical constraints. *Int J Electr Power Energy Syst* 48:48–57
- Holland J (1973) Genetic algorithms and the optimal allocation of trials. *SIAM J Comput* 2(2):88–105
- Huynh T (2008) A modified shuffled frog leaping algorithm for optimal tuning of multivariable PID controllers. *Second international conference on genetic and evolutionary computing*, pp 3–8
- Huynh TH, Nguyen DH (2009) Fuzzy controller design using a new shuffled frog leaping algorithm. In: *Proceedings of the IEEE international conference on industrial technology*, pp 1–6
- Jafari A, Bijami E, Bana HR, Sadri S (2012) A design automation system for CMOS analog integrated circuits using new hybrid shuffled frog leaping algorithm. *Microelectron J* 43(11):908–915
- Jahani R et al (2010) Optimal placement of unified power flow controller in power system by a new advanced heuristic method. *Int J Tech Phys Probl Eng* 2(4):13–18
- Jahani R et al (2011) Optimal parameters of power system stabilizer for minimizing the maximum overshoot using SFLA. *Am J Sci Res* 32(32):58–68
- Karaboga D (2005) An idea based on honey bee swarm for numerical optimization. Technical report TR06, Erciyes University, Engineering Faculty, Computer Engineering Department
- Kavousifard A, Samet H (2011) A novel method based on modified shuffled frog leaping algorithm and artificial neural network for power system load prediction. In: *Emerging intelligent technologies in industry*. Springer, Heidelberg, pp 35–46
- Khorsandi A, Alimardani A, Vahidi B, Hosseini SH (2011) Hybrid shuffled frog leaping algorithm and Nelder–Mead simplex search for optimal reactive power dispatch. *IET Gener Transm Distrib* 5(2):249–256
- Kimiyağhalam A (2012) Application of IBSFLA and BSFLA approaches for locating of fault indicators in distribution networks. *Distrib Netw* 17:1–7
- Kirkpatrick S, Gelatt CD, Vecchi MP (1983) Optimization by simulated annealing. *Science* 220(4598):671–680
- Li J, Pan Q, Xie S (2012) An effective shuffled frog-leaping algorithm for multi-objective flexible job shop scheduling problems. *Appl Math Comput* 218(18):9353–9371
- Li Q (2009) Shuffled frog leaping algorithm based optimal reactive power flow. In: *Proceedings of the international symposium on computer network and multimedia technology*, pp 1–4
- Li X, Luo J, Chen M, Wang N (2012) An improved shuffled frog-leaping algorithm with extremal optimisation for continuous optimisation. *Inf Sci* 192:143–151
- Li Y, Xiu-fen K, Rui-qing H (2011a) Modified shuffled frog leaping algorithm applying to logistics distribution vehicle routing problem. In: *Proceedings of the 4th international conference on biomedical engineering and informatics (BMEI)*, pp 2277–2280
- Li ZY, Yu CX, Zhang ZJ (2011b) Optimal algorithm of shuffled frog leaping based on immune evolutionary particle swarm optimization. *Adv Mater Res* 268–270:1188–1193
- Li Y, Zhou J, Yang L, Qin H, Yang L (2008) The Chaos-based shuffled frog leaping algorithm and its application. In: *Proceedings of the fourth international conference on natural computation*, pp 481–485

- Li Z, Wang Y (2011a) An improved shuffled frog leaping algorithm for TSP. *Adv Multimed Softw Eng Comput* 2:139–144
- Li Y, Zhou J, Zhang Y, Qin H, Liu L (2010) Novel multiobjective shuffled frog leaping algorithm with application to reservoir flood control operation. *J Water Resour Plan Manag* 136(2):217–226
- Lin J, Zhong Y, Zhang J (2012) A modified discrete shuffled frog leaping algorithm for RNA secondary structure prediction. In: *Advances in control and communication*. Springer, Heidelberg, pp 591–599
- Lin J, Zhong Y, Zhang J (2011) Discrete shuffled frog leaping algorithm for RNA secondary structure prediction. In: *Proceedings of the seventh international conference on natural computation*, pp 1489–1493
- Lin MD et al (2007) Scatter search heuristic for least-cost design of water distribution networks. *Eng Optim* 39(7):857–876
- Liping Z, Weiwei W, Han Y, Yefeng X, Yixian C (2012) Application of shuffled frog leaping algorithm to an uncapacitated SLLS problem. *AASRI Conf Comput Intell Bioinform* 1:226–231
- Liu J, Li Z, Hu X, Chen Y, Liu F (2012) Multi-objective dynamic population shuffled frog-leaping biclustering of microarray data. *BMC Genomics* 13(3):S6
- Liu J, Li Z, Hu X, Chen Y (2011) Multi-objective optimization shuffled frog-leaping biclustering. In: *Proceedings of the IEEE international conference on bioinformatics and biomedicine workshops (BIBM)*, pp 151–156
- Luo KP (2012) A shuffled frog leaping algorithm for solving vehicle routing problem. *Appl Mech Mater* 197:529–533
- Luo XH, Yang Y, Li X (2008) Solving TSP with shuffled frog-leaping algorithm. In: *Proceedings of the eighth international conference on intelligent systems design and applications*, pp 228–232
- Malekpour AR, Niknam T (2011) A probabilistic multi-objective daily Volt/Var control at distribution networks including renewable energy sources. *Energy* 36(5):3477–3488
- Malekpour AR, Tabatabaei S, Niknam T (2012) Probabilistic approach to multi-objective Volt/Var control of distribution system considering hybrid fuel cell and wind energy sources using improved shuffled frog leaping algorithm. *Renew Energy* 39(1):228–240
- Nejad HC, Jahani R, Sarlak GR (2011) Applying shuffled frog leaping algorithm for economic load dispatch of power system. *Am J Sci Res* 20(20):82–89
- Niknam T, Farsani A (2010) A hybrid self-adaptive particle swarm optimization and modified shuffled frog leaping algorithm for distribution feeder reconfiguration. *Eng Appl Artif Intell* 23(8):1340–1349
- Niknam T, Nayeripour M (2011) An efficient multi-objective modified shuffled frog leaping algorithm for distribution feeder reconfiguration problem. *Eur Trans Electr Power* 21:721–739
- Niknam T, Narimani MR, Jabbari M, Malekpour AR (2011a) A modified shuffle frog leaping algorithm for multi-objective optimal power flow. *Energy* 36(11):6420–6432
- Niknam T, Zare M, Aghaei J, Farsani EA (2011b) A new hybrid evolutionary optimization algorithm for distribution feeder reconfiguration. *Appl Artif Intell* 25(10):951–971
- Niknam T, Bahmani B, Doagou H (2011c) A new evolutionary algorithm for non-linear economic dispatch. *Expert Syst Appl* 38(10):13301–13309
- Niknam T, Farsani E, Nayeripour M, Firouzi B (2012) A new tribe modified shuffled frog leaping algorithm for multi-objective distribution feeder reconfiguration considering distributed generator units. *Eur Trans Electr Power* 22:308–333
- Pakraves H, Shojaei A (2011) Optimization of industrial CSTR for vinyl acetate polymerization using novel shuffled frog leaping based hybrid algorithms and dynamic modeling. *Comput Chem Eng* 35(11):2351–2365
- Pan QK, Wang L, Gao L, Li J (2010) An effective shuffled frog-leaping algorithm for lot-streaming flow shop scheduling problem. *Int J Adv Manuf Technol* 52(5–8):699–713
- Pasha MFK, Lansey K (2009) Water quality parameter estimation for water distribution systems. *Civ Eng Environ Syst* 26(3):231–248
- Perez I, Gomez-Gonzalez M, Jurado F (2012) Estimation of induction motor parameters using shuffled frog-leaping algorithm. *Electr Eng* 95(3):1–9
- Pu H, Zhen Z, Wang D (2011) Modified shuffled frog leaping algorithm for optimization of UAV flight controller. *Int J Intell Comput Cybern* 4(1):25–39
- Rahimi-Vahed A, Mirzaei AH (2008a) A hybrid multi-objective shuffled frog-leaping algorithm for a mixed-model assembly line sequencing problem. *Comput Ind Eng* 53(4):642–666
- Rahimi-Vahed A et al (2008b) A novel hybrid multi-objective shuffled frog-leaping algorithm for a bi-criteria permutation flow shop scheduling problem. *Int J Adv Manuf Technol* 41(11–12):1227–1239
- Rahimi-Vahed A, Mirzaei AH (2007) Solving a bi-criteria permutation flow-shop problem using shuffled frog-leaping algorithm. *Soft Comput* 12(5):435–452
- Rameshkhah F (2011) Comparison of shuffled frog leaping algorithm and PSO in data clustering with constraint for grouping voltage control areas in power systems. *Eur Trans Electr Power* 21:1763–1782
- Rameshkhah F, Abedi M, Hosseini SH (2010) Clustering of voltage control areas in power system using shuffled frog-leaping algorithm. *Electr Eng* 92(7–8):269–282
- Rao RV (2011) *Advanced modeling and optimization of manufacturing processes*. Springer, London
- Rao RV, Savsani VJ (2012) *Mechanical design optimization using advanced optimization techniques*. Springer, London, pp 5–34
- Richard D (1976) *The selfish gene*. Oxford University Press, Oxford
- Roy P, Chakrabarti A (2011) Modified shuffled frog leaping algorithm for solving economic load dispatch problem. *Energy Power Eng* 03(04):551–556
- Roy P (2011) A new technique to solve minimum spanning tree (MST) problem using modified. In: *Proceedings of the conference on advances in recent technologies in communication and computing*, pp 32–35
- Sardou IG, Banejad M, Hooshmand R, Dastfan A (2012) Modified shuffled frog leaping algorithm for optimal switch placement in distribution automation system using a multi-objective fuzzy approach. *IET Gener Transm Distrib* 6(6):493–502
- Sayed E, Farsangi M, Barati M, Lee Y (2012) A modified shuffled frog leaping algorithm for nonconvex economic dispatch problem. In: *Power and energy society gene*, pp 1–8
- Seyed E et al (2011) SVC multi-objective Var planning using SFL. *Int J Tech Phys Probl Eng* 7(3):76–80
- Shayanfar H, Jahani R, Olamaei J (2010a) Comparison of modified shuffled frog leaping algorithm and other heuristic methods for optimal placement of unified power flow controllers in electrical power systems. *Aust J Basic Appl Sci* 4(11):5590–5598
- Shayanfar H, Jahani R, Olamaei J (2010b) Modified shuffled frog leaping algorithm and other heuristic methods for optimal placement of unified power flow controllers in electrical power systems. *Aust J Basic Appl Sci* 4(11):5590–5598
- Shirvani M, Shakeri P, Behzadipour E, Baghbani I (2012a) PID power system stabilizer design based on shuffled frog leaping algorithm. *Life Sci J* 9(2):1065–1070
- Shirvani M, Shakeri P, Behzadipour E, Baghbani I (2012b) Unified power flow controller design based on shuffled frog leaping algorithm. *Life Sci J* 9(2):1071–1076
- Srinivasa Reddy A, Vaisakh K (2013) Shuffled differential evolution for large scale economic dispatch. *Electr Power Syst Res* 96:237–245
- Tavakolan M (2011) Applying the shuffled frog-leaping algorithm to improve scheduling of construction projects with activity splitting allowed. In: *Proceedings of the management and innovation for a sustainable built environment*, pp 1–9

- Tavakolan M, Ashuri B (2012) Comparison of evolutionary algorithms in non-dominated solutions of time-cost-resource optimization problem. *ASC Annu Int Conf Proc* 48:1–9
- Teekeng W, Thammano A (2011) A combination of shuffled frog leaping and fuzzy logic for flexible job-shop scheduling problems. *Procedia Comput Sci* 6:69–75
- Wang L, Fang C (2011) An effective shuffled frog-leaping algorithm for multi-mode resource-constrained project scheduling problem. *Inf Sci* 181(20):4804–4822
- Wang M, Di W (2010) A modified shuffled frog leaping algorithm for the traveling salesman problem. In: *Proceedings of the sixth international conference on natural computation (Icnc)*, pp 3701–3705
- Wang N, Li X, Chen XH (2010) Fast three-dimensional Otsu thresholding with shuffled frog-leaping algorithm. *Pattern Recognit Lett* 31(13):1809–1815
- Wang YM, Bao Y, Chen J, Li J (2011) A hybrid shuffled frog leaping algorithm for solving no_idle permutation flow shop scheduling problems. *Adv Eng Forum* 1:110–115
- Xu L, Fei M, Jia T, Yang TC (2012) Bandwidth scheduling and optimization using non-cooperative game model-based shuffled frog leaping algorithm in a networked learning control system. *Neural Comput Appl* 21(6):1117–1128
- Xu Y, Wang L, Zhou G, Wang S (2011) An effective shuffled frog leaping algorithm for solving hybrid flow-shop scheduling problem. *Adv Intell Comput* 6838:560–567
- Yammani C, Maheswarapu S, Matam S (2012) Multiobjective optimization for optimal placement and size of dg using shuffled frog leaping algorithm. *Energy Procedia* 14:990–995
- Zhang X et al (2012) Power control algorithm in cognitive radio system based on modified shuffled frog leaping algorithm. *AEU Int J Electron Commun* 66(6):448–454
- Zhang Y, Wang B (2010) Optimal viewpoint selection for volume rendering based on shuffled frog leaping algorithm. In: *Proceedings of the IEEE international conference on progress in informatics and computing*, pp 706–709
- Zhen Z et al (2007) A novel memetic algorithm for global optimization based on PSO and SFLA. *Adv Comput Intell* 4683:127–136
- Zhen Z, Wang D, Liu Y (2009) Improved shuffled frog leaping algorithm for continuous optimization problem. In: *Proceedings of the IEEE congress on evolutionary computation*, pp 2992–2995
- Zhijin Z, Keqiang Y, Zhidong Z (2008) Discrete shuffled frog leaping algorithm for multi-user detection in DS-CDMA communication system. In: *Proceedings of the 11th IEEE international conference on communication technology*, pp 421–424