A Modified Shuffled Frog Leaping Algorithm for Nonconvex Economic Dispatch Problem

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***Abstract*—This paper presents a new approach to Economic Dispatch (ED) problems with nonconvex cost functions using Shuffled Frog Leaping (SFL) algorithm. The practical ED problems have nonconvex cost functions with equality and inequality constraints that makes the problem of finding the global optimum difficult using any optimization approaches. In this paper, the standard SFL is improved to deal with the equality and inequality constraints in the ED problem. To validate the results obtained by proposed SFL, a modified SFL is adopted from the literature and applied for comparison. Also, the results obtained by the SFL algorithms are compared with other approaches reported in the literature. The results show that the proposed SFL produces better solutions for two study systems due to extra diversification provided by the algorithm.**

***Index Terms*—Shuffled Frog Leaping algorithm, economic dispatch, nonsmooth cost functions.**

I. Introduction

OVER the last decades there has been a growing interest in algorithms inspired by the observation of natural phenomenon. It has been shown by many researchers that these algorithms are good replacement tools to solve complex computational problems. Various heuristic approaches have been adopted by researchers including genetic algorithm, tabu search, simulated annealing, ant colony, immune system, particle swarm optimization (PSO), gravitational search algorithm, Shuffled Frog Leaping (SFL) algorithm, etc.

The SFL can be classified as a swarm intelligence, which was developed by Eussuf and Lansey in 2000 in determining the optimal discrete pipe sizes for new pipe networks and for network expansions [1]. Due to its advantages, the SFL is being researched and utilized in different subjects by researchers around the world. Some researchers have shown that the standard SFL cannot converge properly and several modifications are proposed to overcome the difficulty associated with the standard SFL in [2]-[7]. The PSO and SFL are combined to form a new mimetic algorithm in [2]. To enhance the stability and global search ability of the SFL algorithm, a cognition component is introduced by Zhang, *et al.* in [3]. To improve the performance of the SFL algorithm, a chaos search is combined with SFL by Li, *et al.* in [4]. In [5], a new frog leaping rule is introduced and the direction and the length of each frog's jump are extended by emulating frog's perception and action uncertainties. Zhen, *et al*. in [6], introduced a new leaping rule as well as giving a new way for dividing the population.

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To overcome the difficulties with the SFL, in this paper, a modified SFL (MSFL) is presented by increasing the local search ability of the algorithm. The issue of exploration and exploitation is taken into account by a frog leaping rule for local search and a mimetic shuffling rule for global information exchange. To show the effectiveness of the proposed algorithm, MSFL is tested on economic dispatch (ED) problem which is one of the most important problems to be solved in the operation and planning of a power system [7]. The primary objective of ED problem is to determine the optimal combination of power outputs of all generating units so that the required load demand at minimum operating cost is met while satisfying system equality and inequality constraints. In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient method, and dynamic programming method, etc. However many mathematical assumptions such as convex, quadratic, differentiable and linear objectives and constraints are required to simplify the problem.

The practical ED problem with ramp rate limits, prohibited operating zones, valvepoint effects and multi-fuel options is represented as a non-smooth or nonconvex optimization problem with equality and inequality constraints and this makes the problem of finding the global optimum difficult and cannot be solved easily by conventional methods.

Since ED is a problem with high complexity, a considerable amount of work has been adopted by researchers to solve a practical ED problem by considering different nonconvex cost functions using various heuristic approaches such as genetic algorithm (GA) [8]-[12], simulated annealing [13], artificial neural network [14]-[16], tabu search [17], evolutionary programming [18]-[22], PSO [23]-[27], ant colony optimization [28]-[29], and differential evolution [30]-[31].

This paper uses MSFL as an alternative approach to solve the nonconvex ED problems. The results obtained by MSFL are compared with those obtained by other approaches reported in the literature which shows the superiority of the

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proposed method over the other approaches reported in the literature.

The paper is organized as follows: to make a proper background, the standard SFL and the proposed SFL are explained in Section II. The optimization problem is formulated in Section III and the study systems are given in Section IV. The results of the MSFL applied in study systems are given in Section V and conclusions are drawn in Section VI.

II. Overview of SFL Algorithms

The SFL is motivated from the simulation of natural mimetic. This optimization approach updates the population of frogs by applying an operator according to the fitness information obtained from the environment so that the population of frogs can move towards better solution spaces. The standard SFL and the proposed MSFL are explained below.

A. Standard SFL Algorithm

In the SFL the population of the frogs is divided into different groups referred to as memeplexes [1]-[6]. Each memeplex has different culture by performing a local search. Each frog has its own idea and can be influenced by the ideas of other frogs during the iterative shuffling process of mimetic evolution following by passing the ideas among memeplexes in a shuffling process. The principle of SFL can be summarized in Figs. 1-2.

As Fig. 1 shows at the first step, n frogs ($P=\{X_1, X_2, \ldots, X_n\}$) are generated randomly within the search space. For d-dimensional problems (d variables), the position of the i-th frog in the search space is represented as $X_i=[x_{i1}, x_{i2}, \ldots, x_{id}]^T$. The frog's position is evaluated using a suitable objective (fitness) function. After evaluating, the frogs are sorted in a descending order according to their fitness. The frog with the global best fitness is identified as X_g. The entire group can be divided into m memeplexes, each of which consisting of q frogs, which satisfy $n=m\times q$. The strategy of division is as follows: the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m-th frog goes to the m-th memeplex, and (m +1)-th frog goes back to the first memeplex, etc. Within each memeplex, the frogs with the best and the worst fitness are identified as X_b and X_w, respectively. The local search block of Fig. 1 is shown in Fig.2.

According to Fig.2, during memeplex evolution, the worst frog X_w leaps toward the best frog X_b, based on the following leaping rule:

$$D_i = rand() \times (X_b - X_w) \tag{1}$$

$$X_w(new) = X_w(old) + D_i \qquad D_{\min} \le D_i \le D_{\max} \tag{2}$$

where $rand()$ is a uniformly distributed random number in the interval [0, 1]. If the repositioning process produces a frog with better fitness, it replaces the worst frog. Otherwise, the process is repeated with respect to the global best frog (X_g) with the best fitness across the memeplexes (X_g replaces X_b). In case of no improvement, a new frog within the feasible space is randomly generated to replace the worst frog. Based on Fig. 1, the evolution process is continued until the termination criterion is met. The termination criterion could be the number of iterations or when a frog of optimum fitness is found.

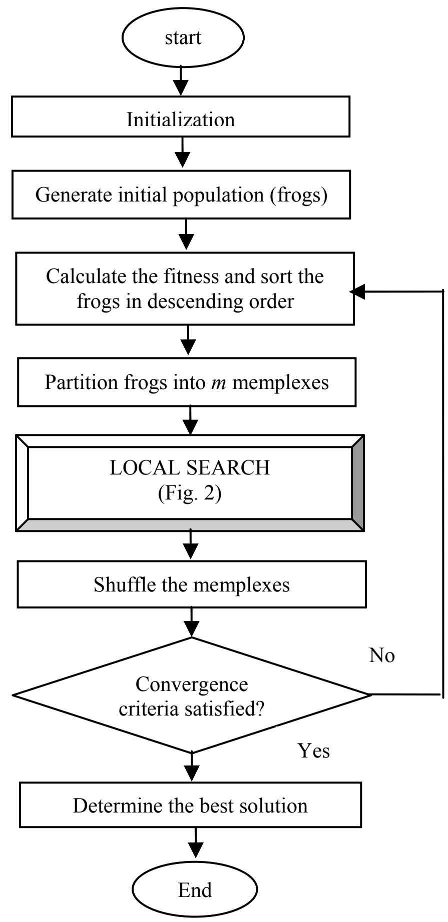

Fig. 1. General principle of the SFL algorithm.

B. The proposed MSFL Algorithm

In the population based heuristic algorithms two common aspects should be taken into consideration: exploration and exploitation. The exploration is the ability to investigate the search space for finding new and better solutions, whereas the exploitation is the ability of finding the optima around a good solution. To have a high performance search, an essential key is having a suitable tradeoff between exploration and exploitation.

The SFL may fell into a local optimum early in a run on some optimization problems. In other words, the algorithm approaches the neighborhood of the global optimum but for some reason it fails to converge to the global optimum. The stagnation could be due to the following reason:

In the standard SFL, only the position of the worst frog of each memeplex is changed according to (1)-(2). This issue makes the algorithm having an insufficient learning mechanism. In other words, the better frogs have fewer learning chances, unless that the worse frog catches up on them. This learning mechanism leads the algorithm to be trapped in a local optimum easily.

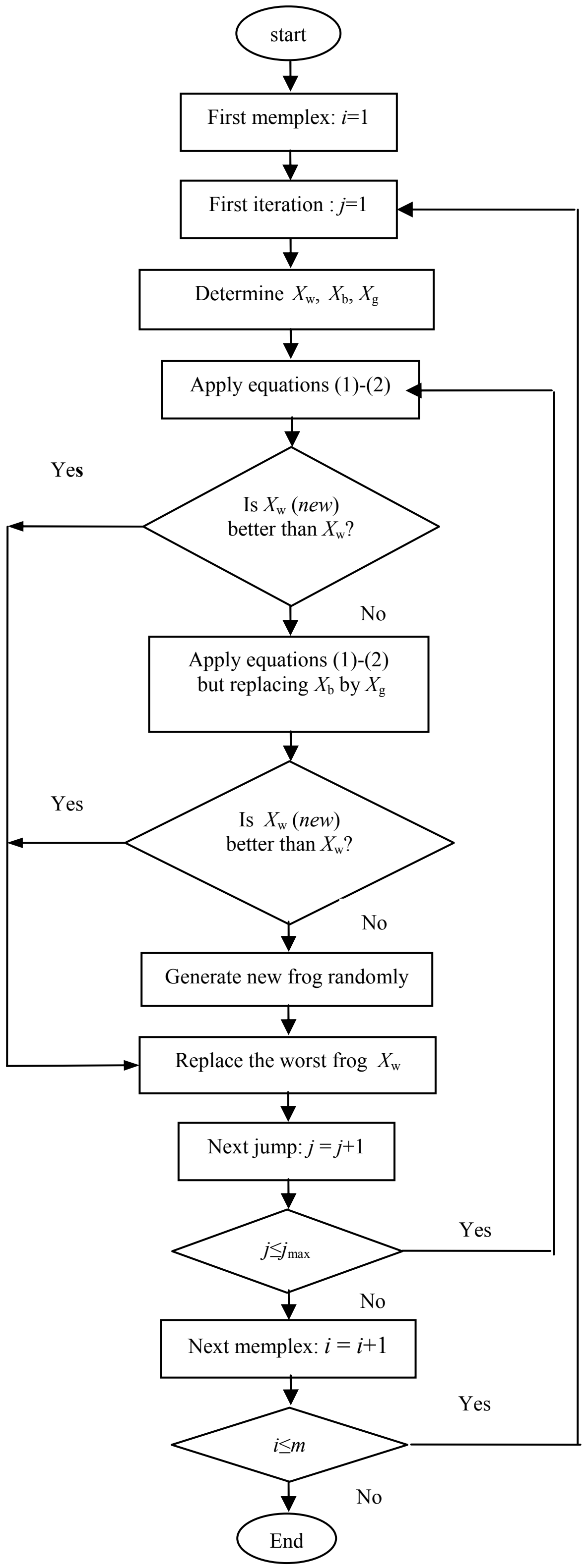

Fig. 2. Local search block of Fig. 1.

To overcome the above problem, a suggestion is given below. This suggestion is based on the modification in [5], where the authors define an uncertainty terms since in nature, the worst frog cannot jump exactly to its target position. Due to imperfect perception, a modified frog leaping rule is defined as:

$$D = r \times c \times (X_b - X_w) + W \tag{3}$$

$$W = [r_1 w_{1,\max}, r_2 w_{2,\max}, \ldots, r_d w_{d,\max}]^T \tag{4}$$

$$W_{\max}^{iteration} = \lambda^{iteration} W_{\max}^{0} \tag{5}$$

$$X_w(new) = \begin{cases} X_w + D & if\ \|D\| \le D_{\max} \\ X_w + \dfrac{D}{\sqrt{D^T D}} D_{\max} & if\ \|D\| > D_{\max} \end{cases} \tag{6}$$

where r is a uniformly distributed random number in the interval [0, 1]; c is a constant chosen in the range between 1 and 2; r_i $(1 \le i \le d)$ are uniformly distributed random numbers in the interval [-1, 1]; $w_{i,\max}$ $(1 \le i \le d)$ is the maximum allowed perception and action uncertainties in the i-th dimension of the search space, the maximum uncertainties are exponentially decreased according to (5) where λ is a decay factor in the range between 0 and 1; $W_{\max}^{0}$ is the initial maximum uncertainties that can be chosen equal to 10-20 percent of the initial range of each dimensions and D_{max} is the maximum allowed distance of one jump.

The rest of the algorithm is similar to the standard SFL as explained in the previous subsection.

With the above given modification in [5], the algorithm may trap in the local optimum since there is a still insufficient learning mechanism (as it is evident in Section V Table I). In this paper, learning mechanism is improved while keeping the uncertainty term the same, which are defined in (4)-(5).

Instead of learning from the best frog, all the frogs are considered based on the following equation:

$$D_i = r \times c \times (X_i - X_w) + W \tag{7}$$

Then, the new position of the frog is obtained as follows:

$$X_w(new) = X_w(old) + D_i \qquad D_{\min} \le D_i \le D_{\max} \tag{8}$$

If the repositioning process produces a frog with better fitness, it replaces the worst frog. Otherwise, the process is repeated with respect to the global best frog (X_g) with the current flog X_i. In the case of improvement, it replaces the worst frog. In the case of no improvement, the algorithm goes toward stagnation and it needs a new movement to explore the new position in the search space. First, a new frog within the feasible space is randomly generated to replace the worst frog. Then, X_i is leaped to explore a new position as follows:

$$D_i = r \times c \times (X_g - X_i) + W \tag{9}$$

Then, the new position of the frog is obtained based on the following equation:

$$X_i(new) = \begin{cases} X_i + D_i & if\ \|D_i\| \le D_{\max} \\ X_i + \dfrac{D_i}{\sqrt{D_i^T D_i}} D_{\max} & if\ \|D_i\| > D_{\max} \end{cases} \quad (10)$$

If the repositioning process produces a frog with better fitness, it replaces X_i. Otherwise the algorithm goes to the next jump and the evolution process is continued until the termination criterion is met. The termination criterion could be the number of iterations or when a frog of maximal fitness is found. The principle of the MSFL is given by Fig. 3.

III. PROBLEM FORMULATION

For convenience in solving the ED problem, the unit generation output is usually assumed to be adjusted smoothly and instantaneously. Practically, the operating range of all online units is restricted by their ramp-rate limits for enforcing the units' operation smooth between two adjacent specific operation periods. In addition, the prohibited operating zones, valve-point effects and multi-fuel options must be taken into account. The traditional and practical ED is explained below:

A. Traditional ED Problem with Smooth Cost Functions

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function. The primary objective of the ED problem is to determine the optimal combination of power outputs of all generating units so that the required load demand at minimum operating cost is met while satisfying system equality and inequality constraints. Therefore, the ED problem can be described as a minimization process with the following objective:

$$\min F = \sum_{i=1}^{N_G} F_i(P_{Gi}) = \sum_{i=1}^{N_G} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \quad (11)$$

subject to

$$\sum_{i=1}^{N_G} P_{Gi} = P_{load} + P_{loss} \quad (12)$$

$$P_{Gi\min} \le P_{Gi} \le P_{Gi\max} \qquad for \quad i = 1,2\ldots, N_G \quad (13)$$

where F is the total generation cost (\$/hr), F_i is the fuel-cost function of generator i (\$/hr), N_G is the number of generators, P_{Gi} is the real power output of generator i (MW), and a_i, b_i and c_i are the fuel-cost coefficients of generator i, P_{load} is the total load in the system (MW), P_{loss} is the network loss (MW) that can be calculated by the B-matrix loss formula, $P_{Gi\min}$ and $P_{Gi\max}$ are respectively the minimum and maximum power generation limits of generator i.

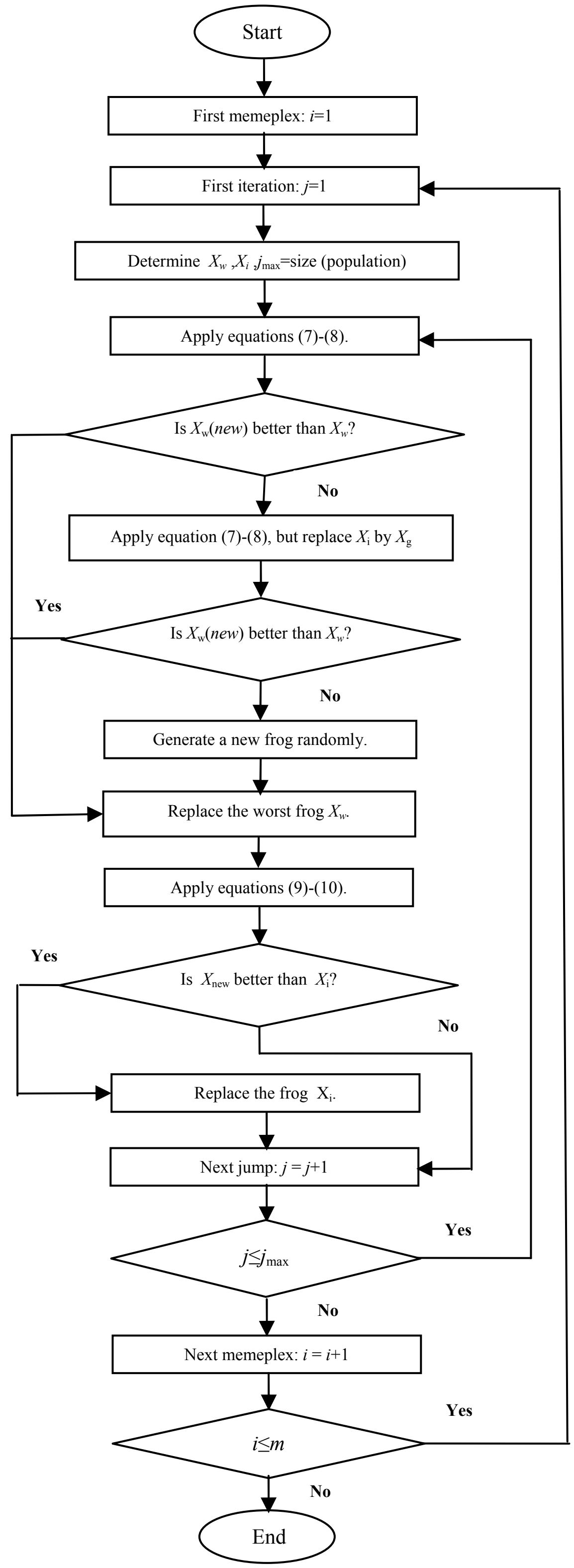

Fig. 3 The proposed MSFL.

B. Practical ED Problem with Nonsmooth Cost Functions

As it is mentioned, a practical ED must take ramp-rate limits, prohibited operating zones, valve-point effects, and multi-fuel options into consideration to provide the completeness for the ED formulation. The resulting ED is a nonconvex optimization problem that has multiple minima, which makes the problem of finding the global optimum difficult:

1) Generator ramp-rate limits. By considering the generator ramp rate limits, the effective real power operating limits are modified as follows:

$$\max(P_{Gi\min}, P_{Gi}^0 - DR_i) \le P_{Gi} \le \min(P_{Gi\max}, P_{Gi}^0 + UR_i)$$
$$i = 1,2,\cdots,N_G$$

$$\frac{\max(P_{Gi\min}, P_{Gi}^0 - DR_i) \le P_{Gi} \le \min(P_{Gi\max}, P_{Gi}^0 + UR_i)}{i = 1,2,\cdots,N_G} \quad (14)$$

where P_{Gi}^0 is the previous operating point of generator *i*, DR_i and UR_i are respectively the down- and up-ramp limits of the generator *i*.

2) Prohibited operating zones. A generator with prohibited regions (zones) has discontinuous fuel-cost characteristics. The discontinuous fuel-cost characteristics of the generators by considering prohibited zones are shown in Fig. 4.

Taking into account the prohibited operating zones, the following constraint is considered in the ED problem:

$$P_{Gi} \in \begin{cases} P_{Gi\min} \le P_{Gi} \le P_{Gi}^{LB1} \\ P_{Gi}^{UB_{k-1}} \le P_{Gi} \le P_{Gi}^{LBk} & k = 2,3,\cdots,N_{PZi} \\ P_{Gi}^{UBk} \le P_{Gi} \le P_{Gi\max} \end{cases} \quad (15)$$
$$i = 1,2\ldots,N_{GPZ}$$

where P_{Gi}^{LBk} and P_{Gi}^{UBk} are respectively the lower and upper boundaries of prohibited operating zone k of generator i in (MW); N_{PZi} is the number of prohibited operating zones of generator i; and N_{GPZ} is the number of generators with prohibited operating zones.

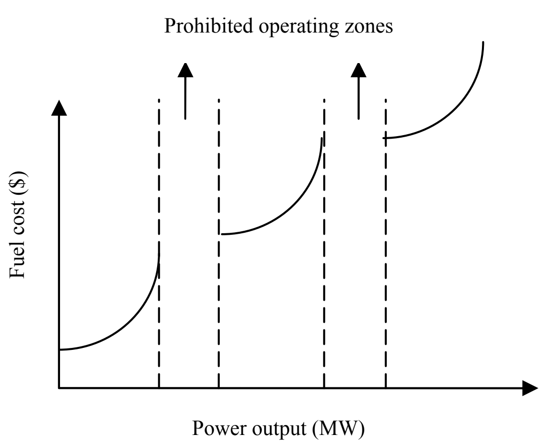

Fig. 4. Input–output curve with prohibited operating zones.

3) Valve-point effects: A generator with multi-valve steam turbines has very different input-output curve compared with the smooth cost function. As each steam valve starts to open, the valve point results in ripples as shown in Fig. 5. To consider the valve-point effects, sinusoidal functions can be added to the quadratic cost functions as follows:

$$F_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| e_i \sin(f_{i(}(P_{Gi\min} - P_{Gi})) \right| \quad (16)$$

where e_i and f_i are the coefficients of generator reflecting valve-point effects.

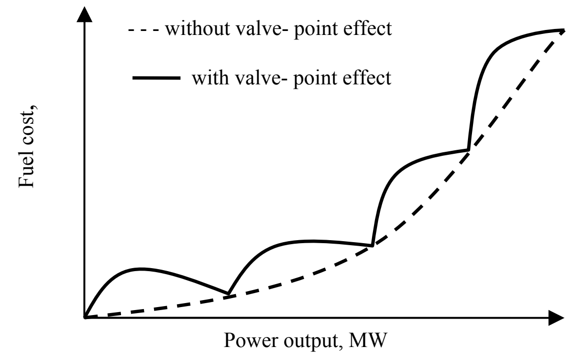

Fig. 5. Piecewise input–output curve under valve-point loading.

IV. Study System

To assess the efficiency of the proposed MSFL, it has been applied to ED problem by considering two test systems having nonconvex solution spaces.

1) The first study system. This study system consists of six generators with ramp-rate limit and prohibited operating zones. The input data for 6-generator system are given in [25] and the total demand is set as 1263 MW. All the generators are having ramp-rate limits. The network losses are calculated by the B-matrix loss formula. It was reported in [27] that the best generation cost reported until now is 15443.0925 \$/h.

2) The second study system. This study system consists of 15 generators with ramp rate limit and prohibited operating zones. The input data of this system are given in [24] and has a total load of 2630 MW. Also, the network losses are calculated by the B-matrix loss formula. The main difference of the study systems 1 and 2 is that the system 2 has many local minima compared to system 1. Thus, the ability of the proposed algorithms is investigated on this larger system. The best generation cost reported until now is 32738.41 \$/h [27].

V. Implementation of MSFL

In order to find the effectiveness and superiority of the MSFL, the test results are compared with the results obtained by other algorithms available in the literature. Therefore, to make the results comparable, the same number of population and iterations available in the literature are used in this paper. Furthermore the suggested SFL in [5] is adopted and applied on the ED problem for comparison with the MSFL. The implementation of MSFL for ED problem of the study systems are given below:

For the study system 1 with six generators, the goal of the optimization is to find the best generation for the six generators. Therefore, each frog is a d-dimensional vector, in which $d = 6$. Initialization is randomly made based on the position of each frog. Population of n frogs is generated randomly, where n is selected to be 20, and m and q are set to be 4 and 5, respectively. The number of iterations is considered to be 50, which is the stopping criterion. Based on the previous experience, c and D are set to 2 and infinity, respectively.

Each frog in the population is evaluated using the objective function defined by (11) subject to (12)-(15) searching for the frogs associated with F_{best}.

To find the minimum cost, the algorithms are run for 50 independent runs under different random seeds. The results obtained by the MSFL and the adopted SFL [5] are shown in Table I, in the first two columns. The rest columns of the table show the obtained results by GCPSO and MPSO reported in [27], binary version of GA, PSO, a modified (new) version of PSO having local random search (NPSO-LRS) reported in [25] and a self-organizing hierarchical PSO (SOH_PSO) reported in [26]. This table shows that the MSFL is performing better than other algorithms in terms of the best generation schedule with minimum network loss in addition to minimum generation cost. Also, the obtained generation schedule is within the generation limits.

The best-so-far of each run is recorded and averaged over 50 independent runs for the MSFL and the adopted SFL. To have a better clarity, the convergence characteristics in finding the minimum cost are given in Fig. 6. This figure shows that the MSFL algorithm performs better due to the extra diversification provided by equations (7)-(10).

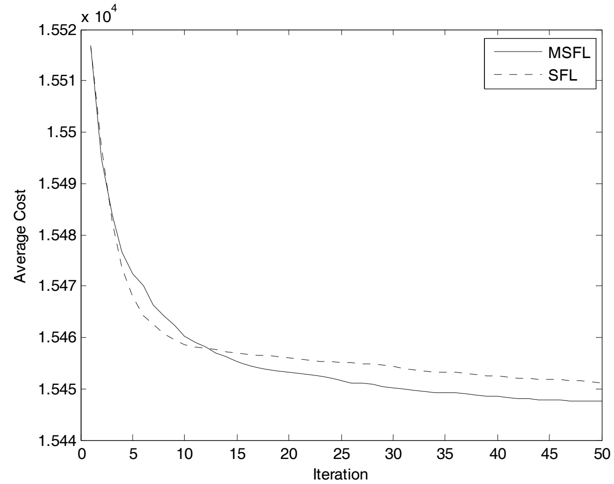

Fig. 6. Convergence characteristics of MSFL and adopted SFL on the average best-so-far in finding the solution in Study System 1.

TABLE I.
COMPARISON OF SIMULATION RESULTS WITH OTHER METHODS (6-GENERATOR SYSTEM).

unit	MSFL	Adopted SFL [5]	GPSO [27]	MPSO [27]	GA [25]	PSO [25]	NPSO-LRS [25]	SOH_PSO[26]
P1	445.0140	443.1332	444.88819	446.48690	474.8066	447.4970	446.9600	438.21
P2	175.5156	178.9638	168.14553	168.66127	178.6363	173.3221	173.3944	172.58
P3	264.2614	262.9462	265	265	262.2089	263.4745	262.3436	257.42
P4	137.3012	136.4721	129.47514	139.49275	134.2826	139.0594	139.5120	141.09
P5	162.7899	167.3992	173.02991	164.0036	151.9039	165.4761	164.7089	179.37
P6	90.4992	86.5589	95.0435	91.74655	74.1812	87.1280	89.0162	86.88
Total generation	1275.38	1275.47	1275.5823	1275.3911	1276.03	1276.01	1275.94	1275.55
Loss	12.389	12.446	12.64113	12.37368	13.0217	12.9584	12.9361	12.5
Load demand	1262.991	1263.024	1263	1263.01746	1263.0083	1263.0516	1263.0039	1263.05
Cost	**15442.5911**	15443.3014	15443.97	15443.0925	15459	15450	15450	15446.02

To investigate the ability of the MSFL in finding the solution and convergence characteristics of the algorithm, the same study is carried out on the second study system which is a larger system. The number of population is considered to be 100 and the number of iteration is considered to be 200, and m and q are set to be 5 and 20, respectively. Also, c and D are set to 2 and infinity, respectively.

The results obtained by the MSFL and SFL are given in Table II, in the first two columns. The rest of the columns of the table show the obtained results by GCPSO and MPSO reported in [27], binary version of GA and PSO reported in [24] and SOH_PSO reported in [26]. The results obtained by all algorithms (listed in Table II) reveals that the best found solution by MSFL is better than other algorithms. In other words, it is clear that dimensionality is not the key factor and the MSFL still outperforms other approaches significantly. The convergence characteristics in finding the minimum cost are given in Fig. 7.

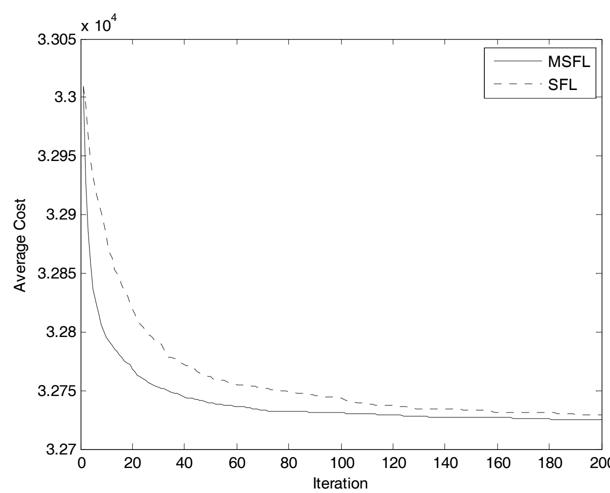

Fig. 7. Convergence characteristics of MSFL and adopted SFL on the average best-so-far in finding the solution in Study System 2.

TABLE II.
COMPARISON OF SIMULATION RESULTS WITH OTHER METHODS (15-GENERATOR SYSTEM).

unit	MSFL	Adopted SFL [5]	GCPSO [27]	MPSO [27]	GA[24]	PSO[24]	SOH_PSO [26]
P1	455.0000	455.0000	449.89252	455	415.3108	439.1162	455.000
P2	380.0000	380.0000	366.99066	380	359.7206	407.9727	380.000
P3	130.0000	130.0000	130	130	104.4250	119.6324	130.000
P4	130.0000	130.0000	130	130	74.9853	129.9925	130.000
P5	170.0000	170.0000	170	170	380.2844	151.0681	170.000
P6	460.0000	460.0000	460	460	426.7902	459.9978	459.96
P7	430.0000	430.0000	430	430	341.3164	425.5601	430.00
P8	71.8386	60.0000	75.88460	92.7278	124.7867	98.5699	117.53
P9	59.0111	68.8952	50.22689	43.0282	133.1445	113.4936	77.90
P10	160.0000	160.0000	160	140.1938	89.2567	101.1142	119.54
P11	80.0000	80.0000	80	80	60.0572	33.9116	54.50
P12	80.0000	80.0000	77.87063	80	49.9998	79.9583	80.00
P13	25.0000	25.0000	25	27.6403	38.7713	25.0042	25.00
P14	15.0000	15.0000	15.8312	20.7610	41.9425	41.4140	17.00
P15	15.0000	17.0261	39.66146	22.2724	22.6445	35.6140	15.00
Total generation	2660.8497	2660.9213	2661.35806	2661.6235	2668.4	2262.4	2662.29
Loss	30.857	30.699	30.86593	29.978	38.2782	32.4306	32.28
The total load	2629.9927	2629.5923	2630.4921	2631.6455	2630.1218	2230.03	2630.01
cost	**32706.5726**	32710.589	32764.4616	32738.41778	33113	32858	32751.39

TABLE III.
AVERAGE, MAXIMUM AND MINMUM COST AND STANDARD DEVIATIONS (SD) OF OBJECTIVE FUNCTION AMONG THE INDEPENDENT RUNS FOR TWO STUDY SYSTEMS.

System / methods	Adopted SFL				MSFL			
	SD	Average _cost	Max_cost	Min_cost	SD	Average _cost	Max_cost	Min_cost
System study 1	4.78	15451.11	15471.11	15443.3014	4.07	15447.60	15460.29	15442.5911
system study 2	19.19	32729.32	32828.40	32710.5869	13.90	32727.03	32761.92	32706.5726

The comparison of the robustness (consistency) and the quality of the solutions obtained by adopted SFL and MSFL is illustrated in Table III. An algorithm is said to be robust, if it gives consistent result during all the independent runs. Table III gives the standard deviations (SD), the average-cost, the worst solution found (Max-cost) and the best solution found (Min-cost) in the results obtained on the independent runs for the study systems 1 and 2. This table illustrates that the MSFL not only provides better solutions but also it is more robust in producing repeatable solutions than the SFL.

VI. CONCLUSIONS

In this paper a Modified Shuffled Frog Leaping (MSFL) algorithm, is proposed to enhance the performance of standard SFL. In SFL, the local search is done through the evolution in memeplexes. The issue of exploration and exploitation is taken into account by a frog leaping rule for local search and a mimetic shuffling rule for global information exchange. In this paper, instead of learning from the best frog, learning mechanism is improved for all the frogs in the population. With the aid of comparisons of the results obtained by MSFL and the results of earlier methods available in the literature, it has been shown that the proposed MSFL is able to find a new optimum solution for the study systems.

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