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# A New Modified Shuffle Frog Leaping Algorithm for Non-Smooth Economic Dispatch

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**Abstract:** This paper presents an effective evolutionary method for solve economic dispatch (ED) with units having prohibited operating zones. ED has been widely used in power system operation and planning for determination of electricity prices. ED problem is a non smooth problem when valve point effects of generation units are considered. With addition the valve point effect and prohibited zones in ED problem this problem complicates more and more respect before and is needed to solve with a strong and accuracy algorithm. This paper presents a very robust algorithm (SLFA) to solve ED problem with valve point effect, furthermore in an attempt to reduce processing time and improve the quality of solutions, particularly to avoid being trapped in local optima, this paper present a modified SLFA that called MSLFA algorithm to solve ED problem. The performance of the MSFLA has been tested on two typical systems consisting of 6 and 40 thermal units and compared with conventional approaches such as genetic algorithm (GA), tabu search algorithm (TSA), PSO and others in literatures. The comparison results show that the efficiency of proposed approach can reach higher quality solution and faster computational time than the conventional methods.

**Key words:** Economic dispatch · Meta-heuristic algorithm · Shuffle frog leaping algorithm · SFLA · ED · Modified SFLA · Valve-point effect · Prohibited zones

## INTRODUCTION

The ED problem is one of the principle issues in power system operations. Essentially, it is an optimization problem and the objective is to decrease the total generation costs, while the total generation should be equal to the total system demand plus the transmission network loss, the generation output of each unit should be between its minimum and maximum limits [1].

Over the years, variant optimization techniques such as the gradient method [2], mix integer programming [3], the lambda iteration method [4], dynamic programming [5], Newton method [4], nonlinear programming [6] and the base point and participation factors method [7] have been proposed to solve the ED problem However in some cases, the foregoing methods fail to provide the global minima and only reach local minima. Moreover, some classical methods cannot handle the integer problems, also these methods suffer from the curse of dimensionality especially in dealing with modern power systems with large number of generators. These shortcomings can be overcome if an evolutionary method is utilized to solve the optimization problem.

Recently, some evolutionary algorithms, such as tabu search (TS) [8], particle swarm optimization (PSO) [9-13], simulated annealing (SA) [14], evolutionary programming (EP) [15–18], genetic algorithms (GA) [19–23], hybrid fuzzy PSO and Nelder-Mead (FAPSO-NM) [24] and evolutionary strategy optimization (ESO) [25] have been widely used to solve economic dispatch problems.

Evolutionary algorithms are optimization techniques that work on a principle inspired by nature systems. SFLA is an evolutionary algorithm which characterized as simple in concept, easy to implement and computationally efficient. In recent years this algorithm employed to solve the optimization problem and the results indicate that this algorithm is very robust and accurate.

Shuffled Frog Leaping Algorithm (SFLA) is a recent memetic meta-heuristic algorithm proposed by Eusuff and Lansey in 2003 [26]. The SFL algorithm involves a set of frogs that cooperate with each other to achieve a unified behavior for the system as a whole, producing a robust system capable of finding high quality solutions for problems with a large search space such as ED problem. The algorithm is used to calculate the global optima of many problems and proves to be a very efficient

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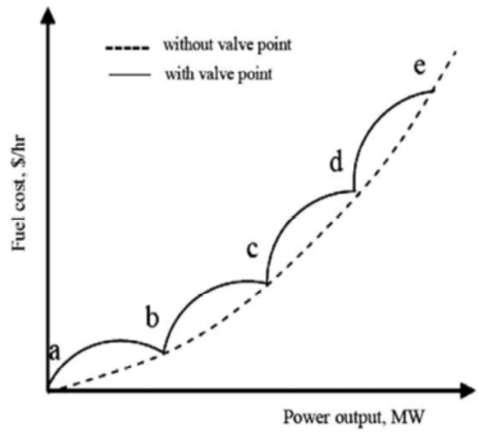



Fig. 1: Cost function of a generator with valve-points

algorithm. SFLA has a very simple, robust and fast algorithm. However, the traditional SLFA often suffers from the problem o f being trapped in local optima. In order to avoid this problem, this paper presents a new modified evolutionary optimization algorithm based on SLFA algorithm that a new mutation is employed in it and called modified Shuffled Frog Leaping Algorithm (MSLFA).

Eventually, the proposed algorithm is applied to test systems consisting of 6 and 40 thermal units, whose fuel cost functions are computed considering the effect of valve-point. The results obtained by the MSFLA are compared with those obtained by other methods. The compression results showed that the proposed method was capable of obtaining accurate and acceptable solutions. Also to validate the obtained results, they are also compared with original SLFA method. Simulation results demonstrate that MSLFA algorithm is superior to other algorithms in literatures. The remained paper is organized as follows: Section 2 formulates the ED problem. Section 3 depicts the principle of original SLFA and modified SLFA problem. Section 4 explains the MSFLA for solving ED problem. Section 5 presents the simulation results. Lastly, conclusion is given in Section 6.

**Formulation of Economic Dispatch Problem:** The mathematical formulation of the ED problem is a famous optimization problem. This can often be formulated as follows:

$$\min f(X) = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i$$
$$X = [Pg_1, Pg_{2,} ....Pg_{Ng}] \quad (1)$$

This objective function will minimize the total system costs, where $f(X)$ is the total generation cost, $a_i$, $b_i$ and $c_i$ are the cost function coefficients of the $i^{th}$ unit, $P_{gi}$ is the real power generation of unit I, Ng is the total number of generation units and X is a control variable vector.

Since the bold line in Figure. 1 gives a more pragmatic approximation for the cost function of generators, it will be used instead of the quadratic function. The ripples in the bold-line cost function curve indicate the effects of the valves. As shown in Figure.1, the curve contains higher order non-linearity rather than the smooth cost function due to the valve-point effects. In order to obtain a more accurate model, which takes into account of the valve-point effects, the cost function is modified to include the ripple curve. This can be done by adding sinusoidal functions to the quadratic function as follow [27]:

$$\min f(X) = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| d_i \times \sin(e_i \times (P_{gi}^{\min} - P_{gi})) \right| \quad (2)$$

**Constraints**

**Output Generator Constraints:**

$$P_{gi\min} \le P_{gi} \le P_{gi\max}$$

$P_{gi\max}$ and $P_{gi\min}$ are the maximum and minimum active power values of i$^{th}$ generator respectively.

**Power Balance Constraint:**

$$\sum_{j=1}^{NG} P_j = P_L + P_D \quad (3)$$

$P_L$ is computed using B-coefficients matrix and it is described by the following equation:

$$P_L = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00} \quad (4)$$

Where $B_{ij}$ is the $I, j^{th}$ element of the loss coefficient square matrix. $B_{i0}$ is the $i^{th}$ element of the loss coefficient vector. $B_{00}$ is the loss coefficient constant.

**Ramp Rate Constraint:** The generation output of a practical generator cannot be adjusted instantaneously without limits. The operating range of all on-line units is restricted by their ramp rate limits during each dispatch period. Therefore, the subsequent dispatch output of a generator should be limited between the constraints of up and down ramp rates.

$P_{i(t)} + P_{i(t-1)} \leq UR_i$
$P_{i(t-1)} + P_{i(t)} \geq DR_i$

Where $P_{i(t)}$, the output power of generator $i$ at current dispatch, $P_{i(t-1)}$ is the output power at previous dispatch, $UR_i$ is the up ramp limit of generator $i$, $DR_i$ is the down ramp limit of generator $i$. It is necessary to note that in this paper ramp rate, is not considered.

**Prohibited Operating Zones:** A unit with prohibited operating zones has discontinuous input–output characteristics. Since it is difficult to determine the actual prohibited zone by real performance testing or operating records, so normally the best economy is achieved by keep away from operation in areas that are in actual operation. Therefore it is necessary to determine a mathematic formulation for prohibited zones. Hence mathematically the feasible operating zones of unit can be depicted as follows:

$$P_i \in \begin{cases} P_i^{\min} \leq P_i \leq P_{i1}^L \\ P_{ik-1}^U \leq P_i \leq P_{ik}^L \\ P_{izi}^U \leq P_i \leq P_i^{\max} \end{cases} \quad (5)$$

Here $zi$ is the number of prohibited zones in $i^{th}$ generator curve, k is the index of prohibited zone of $i^{th}$ generator, $P_{ik}^L$ is the lower limit of $k^{th}$ prohibited zone and $P_{ik}^U$ is the lower limit of $k^{th}$ prohibited zone of $i^{th}$ generator.

**Modified Shuffle Frog Leaping Algorithm:** The economic dispatch problem is a non-linear optimization problem, furthermore with considering the valve point effect non linearity degree and numbers of local optima are increased. Therefore it is necessary to solve this problem with a very robust and accurate algorithm to prevent from trapped in local optima and converges to global optimum result in proper time. SFLA is a memetic meta-heuristic algorithm that is based on populations of frogs in nature searching for food (Eusuff, Lansey, & Pasha). It is a decline based stochastic search method that begins with an initial population of frogs whose characteristics, known as memeplex, represent the decision variables. An initial population of F frogs is created randomly. For K-dimensional problems (K variables), a frog i is represented as $X_i = (x_{i1}, x_{i2}, \ldots x_{ik})$, it is necessary to note that in this study number variable equals to number of generators. Afterwards, the frogs are sorted in a decreasing order according to their fitness. In SFLA, the total population is divided into groups (memeplexes)

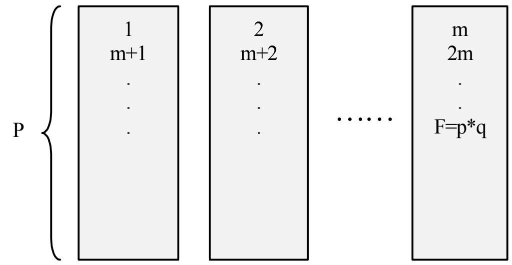



Fig. 2: Dividing F frogs into the q memeplexes

that search independently. In this process, the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog m goes to the $q^{th}$ memeplex and frog $m$+1 goes to the first memeplex and so on that have shown in figure 2.

In the each memeplex, the frogs with the best and the worst fitnesses are considered as $X_b$ and $X_w$, respectively. Also, the frog with the best fitness in all memeplexes is considered as $X_g$. Then, a process similar to particle swarm optimization (PSO) is applied to improve only the frog with the worst fitness (not all frogs) in each iterate. Correspondingly, the location of the frog with the worst fitness is regulated as follows:

$$\text{Change in the position } V_i = rand(\,) \times (X_b - X_w) \quad (6)$$

New location of $X_w$ = current location of

$$X_w + V_i \;;\; -V_{\max} \leq V_i \leq V_{\max} \quad (7)$$

Where rand () is a random number between 0 and 1 and $V_{\max}$ is the maximum allowed change in a frog's position. If this process produces a better solution, it substitutes for the worst frog. Otherwise, the calculations in Equations (6) and (7) are repeated. In addition, to provide the opportunity for random generation of improved information, random virtual frogs are generated and replaced in the population if the local search cannot find better solutions respectively in each iterate. After a number of iterations, the different groups combined and share their ideas with themselves through a shuffling process. The local search and the shuffling processes continue until defined convergence criteria are satisfied. This goal of the overall process is to determine global optimal solutions.

Fundamentally, SFLA combines the profits of the local search tool of the Particle Swarm Optimization (PSO)[28] and the idea of mixing information from parallel local searches to move toward a global solution.

These characteristics cause to SLFA is famous as a strong and robust algorithm. However there are some benefits, mentioned for SLFA before, some problems exist for it too, such as possible being trapped in the local optima. In this paper a new strategy is proposed in order to support the SLFA weak points. This new mode called modified shuffle leaping frog algorithm (MSLFA) will be proposed in details in following.

**Modified SLFA Algorithm (MSFLA):** SLFA has some weak points, for example sometimes trapped in local optima point or converge to proper target very late. For solve above problems in this paper recommended a mutation. In each iteration several population are selected randomly and multiple in a stochastic coefficient. Mutation is an operation that adds a vector differential to a population vector of individuals. The fundamental idea behind mutation is a scheme by which it products the test mutated vector. It mutates vectors in each step by adding weighted random vector differentials to them. If the cost of the test vector is better than that of the target, the target vector is substitute for the trial vector in the next generation. In this paper a new approach and robust mutation operator is presented.

Three random frog such as $X_{m1}$, $X_{m2}$, $X_{m3}$ are selected while $m1$ among all memeplexes. In the second step of mutation each element of mutant vector is formed as follow:

$$x_{mut\ j,i} = \begin{cases} x_{g\ i} + L \times (x_{m1\ j,i} - x_{m2\ j,i}) & if \quad rand() \times x_{j,i} \geq x_{j,i} \\ x_{g\ i} + L \times (x_{m1\ j,i} - x_{m3\ j,i}) & otherwise \end{cases} \tag{8}$$

Where:

$i = 1,2,..............,N_{param}$
$j = 1,2,..............,N_{mutation}$

$$X_{mut} = [X_{mut\,1} \\ X_{mut\ 2} \\ . \\ . \\ X_{mut\ N_{mutation}}]$$

$$X_{mut} = [X_{mut\,1,\,smut\,2}\ ..............,x_{mut\ Nparam}] \tag{9}$$

$L$ = *random number between* 0.7 *and* 0.9

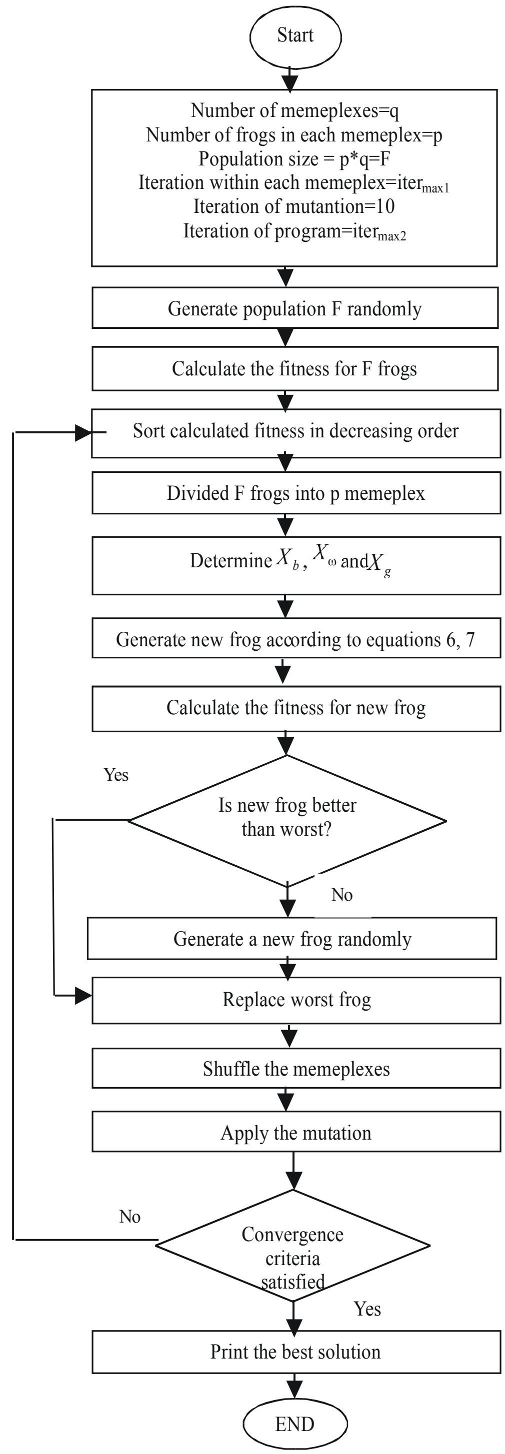



Fig. 3: Algorithm and computational flowchart

*Rand* ( ) is the random number between 0 and 1, $N_{param}$ is the number of parameters and $N_{mutation}$ is the number of mutate vectors. The basic idea behind mutation is a plan by which it generates the trial mutated vector.

In each step, it mutates vectors by adding weighted random vector differentials to them. If the cost of the trial vector is better than that of the $X_g$, the $X_g$ vector is replaced by the trial vector in the next generation. If any element of an individual breaks its constraint then the position of the individual is modified by:

$$x_{mut,i} = \begin{cases} x_{i,\min} & if \quad x_{mut,i} \langle x_{i,\min} \\ x_{i,\max} & if \quad x_{mut,i} \rangle x_{i,\max} \end{cases} \tag{10}$$

A full scale computational flowchart in Figure 3 clarifies the algorithm documentation.

**Application of MSLFA Algorithm to Multi Objective Problem:** This part demonstrates the application of the proposed algorithm for solving the ED problem using MSFLA. It should be noted that the state variables are active power of generators. To implement the proposed algorithm in the ED problem, it is necessary to perform the following steps:

**Step 1:** Define the input data

In this step, the input data including the generators real power borders, fuel cost coefficient of generators, prohibited zone s of generators and loss coefficient are defined.

**Step 2:** The ED problem needs to be converted into an unconstrained one by putting together an augmented objective function incorporating penalty factors:

$$F(X) = f(X) + L_1(\sum_{j=1}^{N_{eq}} (h_j(X))^2) + L_2(\sum_{j=1}^{N_{ueq}} (Max[0, -g_j(X)])^2) \tag{11}$$

$f(X)$ is the objective function described in *Eq*. (8). $N_{eq}$ and $N_{ueq}$ are the number of equality and inequality constraints, respectively. $h_j(X)$ and $g_j(X)$ are the equality and inequality constraints, respectively. $L_1$ and $L_2$ are the penalty factors. Since the constraints should be met, the values of the parameters should be high. In this paper the values have been considered 1000.

**Step 3:** an initial population $X_j$ which must meet constraints, is generated randomly as follows:

$$\text{Population} = \begin{bmatrix} X_1 \\ X_2 \\ \dots \\ X_F \end{bmatrix} \tag{12}$$

$$X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,N}] \tag{13}$$

$$X_i = [Pg_1, Pg_{21} \dots Pg_{NG}] \tag{14}$$

Where:

*Ng = number of generator*

$x_{i,j} = rand(.)*(x_{j,\max} - x_{j,\min}) + x_{j,\min}$

$$j = 1,2,3,\dots, NG \,;\, i = 1,2,3,\dots, \textit{number of frogs} \tag{15}$$

Where, $x_j$ is the position of the $j^{th}$ state variable, *rand* () is a random function generator between 0 and 1 and F is the number of frogs.

**Step 4:** Calculate the objective function value

**Step 5:** Sort the initial population based on the objective function values with decreasing manner.

**Step 6:** dividing sorted generate population in memeplexes by following process, the first population goes to the first memeplex, the second population goes to the second memeplex, population $q_{th}$ goes to the $q_{th}$ memeplex and population q +1 goes back to the first memeplex, etc.

**Step 7:** Select best and worst population in each memeplex and generate the $X_b$ and $X_w$ for them respectively. Also the frog with the global best fitness in all memeplexes is identified as $X_g$.

**Step 8:** A process is applied to improve only the frog with the worst fitness according to equation (7), If this process produces a better solution, it replaces the worst frog. Otherwise, a new population is randomly generated to replace that population. This process continues for a specific number of iterations ($\text{itetation}_{\max 1}$).

**Step 9:** If any element of an individual breaks its inequality constraints then the position of the individual is fixed to its maximum/minimum operating point.

Therefore, this can be formulated as:

$$X_{i,j}^{k+1} = \begin{cases} x_{i,j}^{k+1} & if \quad x_{j,\min} \langle x_{i,j}^{k} \langle x_{j,\max} \\ x_{j,\min} & if \quad x_{i,j}^{k} \langle x_{j,\min} \\ x_{j,\max} & if \quad x_{i,j}^{k} \rangle x_{j,\max} \end{cases} \tag{16}$$

**Step 10:** in this section all memeplexes combined and sorted again.

**Step 11:** apply the mutation.

**Step 12:** If the current iteration number ($iteration_{max2}$) reaches the predetermined maximum iteration number, the search procedure is stopped, otherwise goes to Step 6.

**Step 13:** The last $X_g$ is the solution of the problem.

**Simulation Results:** In order to illustrate the efficiency and robustness of the proposed MSLFA algorithm, this algorithm performed on 40 and 6 unit systems, also obtained results are compared with original SLFA algorithm and other algorithm in literatures. Test results show the superiority of the proposed approach over other algorithms. The parameters required for implementation of the MSFLA algorithm are number of frogs in each memeplex (p), number of memeplexes (q), number of iteration for local exploration ($iteration_{max1}$) and number of iteration for global exploration $iteration_{max2}$ and number of mutation iteration. As MSFLA is a relatively new algorithm, there is no theoretical basis for parameters adjusting. We have to resort to experiments. To balance between efficiency and exploration capability, extensive experiments need to be conducted with different adjusts of parameters. In this paper, the best values for the aforementioned parameters are obtained by 100 times MSFLA algorithm running and shown in table. 6.

**Case study 1:** At the first case study 6 unit system [29] is considered. Table 2 provides the parameters associated with the generating units, it is necessary to note that in this case valve point effect is not considered. The system has 6 units that supply a system demand of 1263MW. All units, have prohibited operating zones that given in Table 2.

Table 3 show the best fuel cost obtained by proposed algorithm as compared to GA [30], CPSO [31],APSO[32],PSO[30], TSA [33], AIS [34], DSPSO-TSA [33], MTS [35].

For more validation to proposed algorithm, the obtained results from five different trials are show in Table 4.

The performance of MSFLA algorithms is judged through 50 trials to show the robustness and accurate of proposed algorithm to solve ED problem. The best result, worst result, mean value and standard deviation are shown in figure 4 and compare with original SFLA.

Table 1: MSLFA algorithm parameters

| | |
|---|---|
| Number of frogs | 10 |
| Number of memeplex | 5 |
| Iteration max 1 | 50 |
| Iteration max 2 | 100 |
| Iteration of mutation | 10 |

Table 2: Cost curves and limits for 6 unit power plant

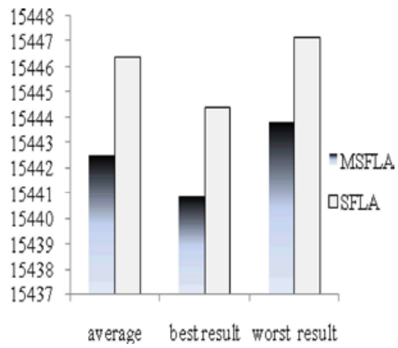
| Unit | a | b | c | Pmin | Pmax | zone1 | zone2 |
|---|---|---|---|---|---|---|---|
| G1 | 0.007 | 7 | 240 | 100 | 500 | [210-240] | [350-380] |
| G2 | 0.0095 | 10 | 200 | 50 | 200 | [90-110] | [140-160] |
| G3 | 0.009 | 8.5 | 220 | 80 | 300 | [150-170] | [210-240] |
| G4 | 0.009 | 11 | 200 | 50 | 150 | [80-90] | [110-120] |
| G5 | 0.008 | 10.5 | 220 | 50 | 200 | [90-110] | [140-150] |
| G6 | 0.0075 | 12 | 190 | 50 | 120 | [75-85] | [100-105] |

Table 3: Results found by the MSFLA and other comparisons methods for 6 units system

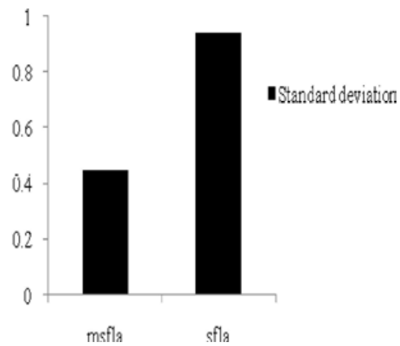
| Power Output | GA[30] | CPSO[31] | PSO[30] | APSO[33] | AIS[34] | TSA[33] | MTS[35] | DSPSO-TSA[33] | SFLA | MSFLA |
|---|---|---|---|---|---|---|---|---|---|---|
| PG1 | 474.8066 | 434.4295 | 447.497 | 446.6686 | 458.2904 | 449.3651 | 448.1277 | 439.2935 | 449.19266 | 449.1444 |
| PG2 | 178.6363 | 173.3231 | 173.3221 | 173.1556 | 168.0518 | 182.252 | 172.8082 | 187.7876 | 173.0893 | 173.0537 |
| PG3 | 262.2089 | 274.4735 | 263.4745 | 262.826 | 262.5175 | 254.2904 | 262.5932 | 261.026 | 266.03873 | 266.0012 |
| PG4 | 134.2826 | 128.0598 | 139.0594 | 143.4686 | 139.0604 | 143.4506 | 136.9605 | 129.4973 | 127.14984 | 127.1123 |
| PG5 | 151.9039 | 179.4759 | 165.4761 | 163.914 | 178.3936 | 161.9682 | 168.2031 | 171.7101 | 174.293581 | 174.2513 |
| PG6 | 74.1812 | 85.9281 | 87.128 | 85.3437 | 69.3416 | 86.0185 | 87.3304 | 86.1648 | 85.913156 | 85.86813 |
| Total generation | 1276.03 | 1276 | 1276.01 | 1275.376 | 1275.655 | 1277.345 | 1276.023 | 1275.514 | 1275.6773 | 1275.4312 |
| Ploss(MW) | 13.0217 | 12.9583 | 12.9584 | 12.4216 | 12.655 | 14.3449 | 13.0205 | 13.0421 | 12.67732 | 12.43127 |
| Generation cost | 15459 | 15446 | 15450 | 15444 | 15448 | 15,451.63 | 15450.06 | 15,441.57 | 15444.174 | 15440.9053 |

Table 4: Generator output for least cost in 5 trials for 6 unit power plant

| Power Output | Trial 1 | Trial 2 | Trial 3 | Trial 4 | Trial 5 |
|---|---|---|---|---|---|
| PG1 | 449.1505602 | 449.1509551 | 449.158792 | 449.1467513 | 449.1444264 |
| PG2 | 173.0583095 | 173.058596 | 173.0643789 | 173.0555016 | 173.0537881 |
| PG3 | 266.0059936 | 266.0062932 | 266.0123925 | 266.003025 | 266.0012176 |
| PG4 | 127.1170989 | 127.1174083 | 127.1235065 | 127.1141406 | 127.1123322 |
| PG5 | 174.2567399 | 174.2570813 | 174.2639456 | 174.2534063 | 174.2513772 |
| PG6 | 85.87385797 | 85.87422201 | 85.88154052 | 85.87030264 | 85.86813306 |
| Total generation | 15453.78365 | 15453.81216 | 15454.38369 | 15453.50599 | 15453.33664 |
| Ploss(MW) | 12.46256 | 12.464556 | 12.504556 | 12.44312745 | 12.43127453 |
| Generation cost | 15441.32109 | 15441.34761 | 15441.87914 | 15441.06286 | 15440.90536 |




(a) Mean, best result and worth result




(b) Standard deviation

Fig. 4: The comparison of the proposed algorithm and original SFLA for 40 units system after 100 trials

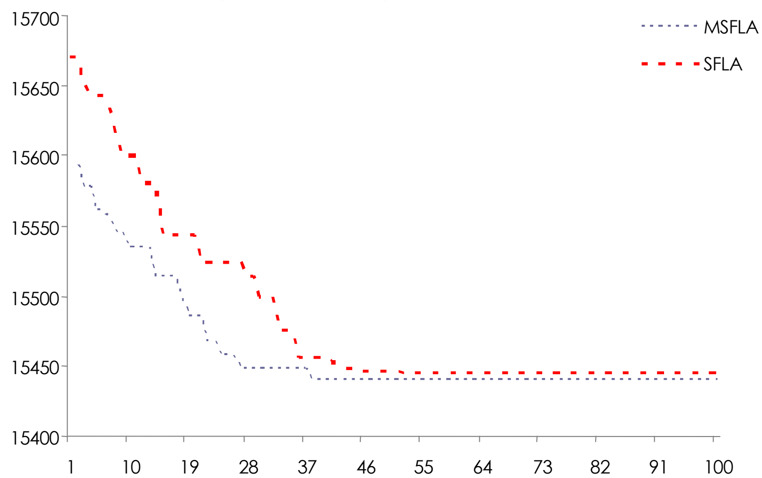



Fig. 5: Compression convergence plot of proposed algorithm and original SFLA

The convergence plots of MSFLA and SFLA for 6 units system are shown in figure 5. It is clear that MSFLA algorithm m converge to lower amount rather than SFLA algorithm in a lower time, it is show the superiority of the MSFLA respect to the original SFLA.

The results obtained from the MSFLA had minimum cost, average cost and maximum generation cost are better than other methods in literatures and original SFLA. The 50 independent trials had converged to optimum solution illustrated in Figure 6.

**Case study 2:** At the second case study 40 units system [36] is considered. Table 5 provides the parameters associated with the generating units and prohibited zones. Also in this case valve point effect is considered. The total load demand is 10500MW and not considering transmission line losses.

Table 6 reports the best dispatch results of the proposed method and other methods from literatures. Evidently, the MSFLA provides less the total generation cost when compared with FAMPSO [37], FAPSO-NM [38], FAPSO[38],SOHPSO[39], DE [40], EP-SQP [41], IFEP [41], MFEP [40], PSO-SQP[41].

For more validation to proposed algorithm, the obtained results from five different trials are show in Table 7.

Table 5: Cost curves and limits for 40 units power plant

| Unit | a | b | c | e | f | Pmin | Pmax | Zone1 | Zone2 | Zone3 |
|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0.0069 | 6.73 | 9.47E+01 | 100 | 8.40E-02 | 36 | 114 | - | - | - |
| G2 | 0.0069 | 6.73 | 9.47E+01 | 100 | 8.40E-02 | 36 | 114 | - | - | - |
| G3 | 0.02028 | 7.07 | 3.10E+02 | 100 | 8.40E-02 | 60 | 120 | - | - | - |
| G4 | 0.00942 | 8.18 | 3.69E+02 | 150 | 6.30E-02 | 80 | 190 | - | - | - |
| G5 | 0.0114 | 5.35 | 1.49E+02 | 120 | 7.70E-02 | 47 | 97 | - | - | - |
| G6 | 0.01142 | 8.05 | 2.22E+02 | 100 | 8.40E-02 | 68 | 140 | - | - | - |
| G7 | 0.00357 | 8.03 | 2.88E+02 | 200 | 4.20E-02 | 110 | 300 | - | - | - |
| G8 | 0.00492 | 6.99 | 3.92E+02 | 200 | 4.20E-02 | 135 | 300 | - | - | - |
| G9 | 0.00573 | 6.6 | 4.56E+02 | 200 | 4.20E-02 | 135 | 300 | - | - | - |
| G10 | 0.00605 | 12.9 | 7.23E+02 | 200 | 4.20E-02 | 130 | 300 | [130-150] | [200-230] | [270-299] |
| G11 | 0.00515 | 12.9 | 6.35E+02 | 200 | 4.20E-02 | 94 | 375 | [100-140] | [230-280] | [300-350] |
| G12 | 0.00569 | 12.8 | 6.55E+02 | 200 | 4.20E-02 | 94 | 375 | [100-140] | [230-280] | [300-350] |
| G13 | 0.00421 | 12.5 | 9.13E+02 | 300 | 3.50E-02 | 125 | 500 | [150-200] | [250-300] | [400-450] |
| G14 | 0.00752 | 8.84 | 1.76E+03 | 300 | 3.50E-02 | 125 | 500 | [200-250] | [300-350] | [450-490] |
| G15 | 0.00708 | 9.15 | 1.73E+03 | 300 | 3.50E-02 | 125 | 500 | - | - | - |
| G16 | 0.00708 | 9.15 | 1.73E+03 | 300 | 3.50E-02 | 125 | 500 | - | - | - |
| G17 | 0.00313 | 7.97 | 6.48E+02 | 300 | 3.50E-02 | 220 | 500 | - | - | - |
| G18 | 0.00313 | 7.95 | 6.50E+02 | 300 | 3.50E-02 | 220 | 500 | - | - | - |
| G19 | 0.00313 | 7.97 | 6.48E+02 | 300 | 3.50E-02 | 242 | 550 | - | - | - |
| G20 | 0.00313 | 7.97 | 6.48E+02 | 300 | 3.50E-02 | 242 | 550 | - | - | - |
| G21 | 0.00298 | 6.63 | 7.86E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G22 | 0.00298 | 6.63 | 7.86E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G23 | 0.00284 | 6.66 | 7.95E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G24 | 0.00284 | 6.66 | 7.95E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G25 | 0.00277 | 7.1 | 8.01E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G26 | 0.00277 | 7.1 | 8.01E+02 | 300 | 3.50E-02 | 254 | 550 | - | - | - |
| G27 | 0.52124 | 3.33 | 1.06E+03 | 120 | 7.70E-02 | 10 | 150 | - | - | - |
| G28 | 0.52124 | 3.33 | 1.06E+03 | 120 | 7.70E-02 | 10 | 150 | - | - | - |
| G29 | 0.52124 | 3.33 | 1.06E+03 | 120 | 7.70E-02 | 10 | 150 | - | - | - |
| G30 | 0.0114 | 5.35 | 1.49E+02 | 120 | 7.70E-02 | 47 | 97 | - | - | - |
| G31 | 0.0016 | 6.43 | 2.23E+02 | 150 | 6.30E-02 | 60 | 190 | - | - | - |
| G32 | 0.0016 | 6.43 | 2.23E+02 | 150 | 6.30E-02 | 60 | 190 | - | - | - |
| G33 | 0.0016 | 6.43 | 2.23E+02 | 150 | 6.30E-02 | 60 | 190 | - | - | - |
| G34 | 0.0001 | 8.95 | 1.08E+02 | 200 | 4.20E-02 | 90 | 200 | - | - | - |
| G35 | 0.0001 | 8.62 | 1.17E+02 | 200 | 4.20E-02 | 90 | 200 | - | - | - |
| G36 | 0.0001 | 8.62 | 1.17E+02 | 200 | 4.20E-02 | 90 | 200 | - | - | - |
| G37 | 0.0161 | 5.88 | 3.07E+02 | 80 | 9.80E-02 | 25 | 110 | - | - | - |
| G38 | 0.0161 | 5.88 | 3.07E+02 | 80 | 9.80E-02 | 25 | 110 | - | - | - |
| G39 | 0.0161 | 5.88 | 3.07E+02 | 80 | 9.80E-02 | 25 | 110 | - | - | - |
| G40 | 0.00313 | 7.97 | 6.48E+02 | 300 | 3.50E-02 | 242 | 550 | - | - | - |

Table 6: Results found by the MSFLA and other comparisons methods for 40 units system

| Algorithm | Minimum cost($) | Maximum cost($) | Mean cost($) |
|---|---|---|---|
| MSLFA | 121412.53 | 121415.26 | 121413.0521 |
| SFLA | 121417.33 | 121418.93 | 121418.174 |
| FAMPSO[39] | 121412.57 | 121415.78 | 121413.3871 |
| FAPSO-NM[40] | 121418.3 | 121419.8 | 121418.803 |
| FAPSO[40] | 121712.4 | 121873.17 | 121778.246 |
| SOHPSO[41] | 121501.14 | 122446.3 | 121853.57 |
| DE[42] | 121416.29 | 121431.47 | 121422.72 |
| EP-SQP[43] | 122323.97 | - | 122379.63 |
| IFEP[43] | 122624.35 | 125740.63 | 123382 |
| MFEP[42] | 122647.57 | 124356.47 | 123484.74 |
| PSO-SQP[43] | 122094.67 | - | 122295.13 |

Table 7: Generator output for least cost in 40 trials for 6 units power plant

| | Trial 1 | Trial 2 | Trial 3 | Trial 4 | Trial 5 |
|---|---|---|---|---|---|
| PG1 | 110.7998 | 110.7979 | 110.8027 | 110.7999 | 110.8027 |
| PG2 | 110.7998 | 110.7998 | 110.8054 | 110.7999 | 110.8054 |
| PG3 | 97.3999 | 97.3999 | 97.3999 | 97.3999 | 97.3999 |
| PG4 | 179.7331 | 179.7331 | 179.7331 | 179.7331 | 179.7331 |
| PG5 | 87.7999 | 87.8 | 87.7999 | 87.7999 | 87.7999 |
| PG6 | 140 | 140 | 140 | 140 | 140 |
| PG7 | 259.5997 | 259.5997 | 259.5997 | 259.5997 | 259.5997 |
| PG8 | 284.5997 | 284.6258 | 284.5997 | 284.5997 | 284.5997 |
| PG9 | 284.5997 | 284.5996 | 284.5997 | 284.5997 | 284.5997 |
| PG10 | 130 | 130 | 130 | 130 | 130 |
| PG11 | 94 | 94 | 94 | 94 | 94 |
| PG12 | 94 | 94 | 94 | 94 | 94 |
| PG13 | 214.7598 | 214.7597 | 214.7598 | 214.7598 | 214.7598 |
| PG14 | 394.2794 | 394.2793 | 394.2794 | 394.2794 | 394.2794 |
| PG15 | 394.2794 | 394.2793 | 395.2794 | 394.2794 | 394.2794 |
| PG16 | 394.2794 | 394.2793 | 396.2794 | 394.2794 | 394.2794 |
| PG17 | 489.2794 | 489.2793 | 489.2794 | 489.2794 | 489.2794 |
| PG18 | 489.2794 | 489.2801 | 489.2794 | 489.2794 | 489.2794 |
| PG19 | 511.2794 | 511.2793 | 511.2794 | 511.2794 | 511.2794 |
| PG20 | 511.2794 | 511.2793 | 512.2794 | 511.2794 | 511.2794 |
| PG21 | 512.2794 | 523.2793 | 523.2794 | 523.2794 | 523.2794 |
| PG22 | 513.2794 | 523.2793 | 524.2794 | 523.2794 | 523.2794 |
| PG23 | 514.2794 | 523.2793 | 525.2794 | 523.2794 | 523.2794 |
| PG24 | 515.2794 | 523.2793 | 526.2794 | 523.2794 | 523.2794 |
| PG25 | 516.2794 | 523.2793 | 527.2794 | 523.2794 | 523.2794 |
| PG26 | 517.2794 | 523.2793 | 528.2794 | 523.2794 | 523.2794 |
| PG27 | 10 | 10 | 10 | 10 | 10 |
| PG28 | 10 | 10 | 10 | 10 | 10 |
| PG29 | 10 | 10 | 10 | 10 | 10 |
| PG30 | 87.7999 | 87.80311 | 87.7999 | 87.7999 | 87.7999 |
| PG31 | 190 | 190 | 190 | 190 | 190 |
| PG32 | 190 | 190 | 190 | 190 | 190 |
| PG33 | 190 | 190 | 190 | 190 | 190 |
| PG34 | 164.7998 | 164.8193 | 164.8 | 164.7998 | 164.7992 |
| PG35 | 194.3978 | 194.3498 | 194.3892 | 194.3976 | 194.3899 |
| PG36 | 200 | 200 | 200 | 200 | 200 |
| PG37 | 110 | 110 | 110 | 110 | 110 |
| PG38 | 110 | 110 | 110 | 110 | 110 |
| PG39 | 110 | 110 | 110 | 110 | 110 |
| PG40 | 511.2794 | 511.2793 | 511.2794 | 511.2794 | 511.2794 |
| Cost($) | 121412.5355 | 121 412.87 | 121412.5815 | 121412.5363 | 121412.5874 |

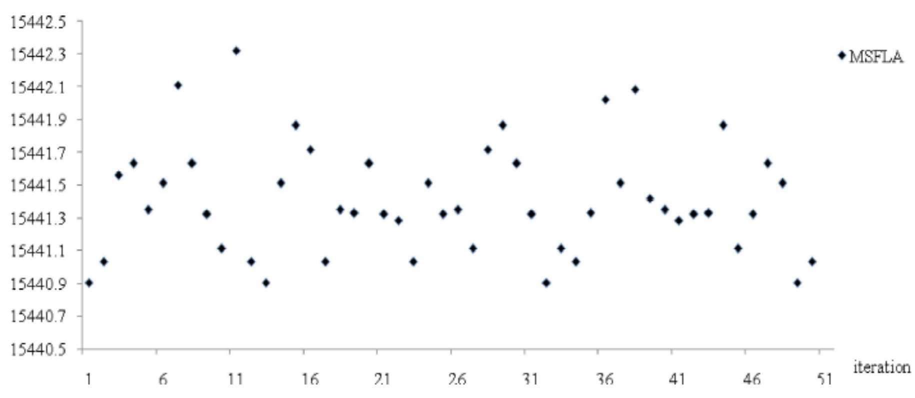



Fig. 6: Convergences curve of 100 independent trials of case study 1.

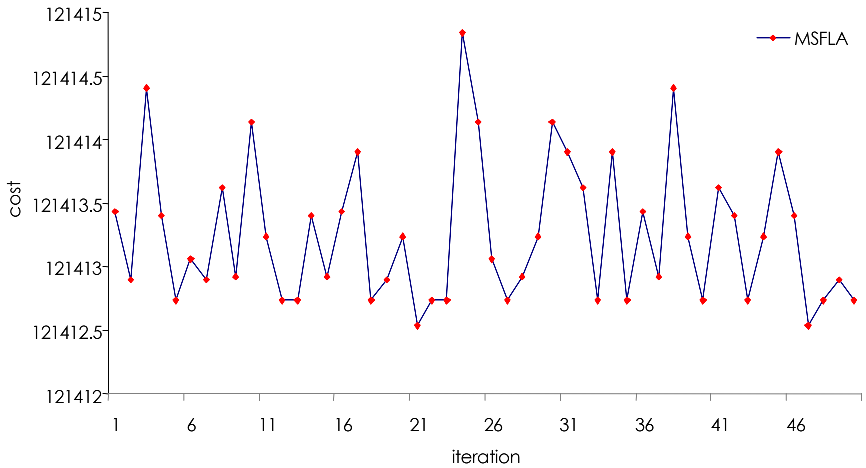



Fig. 7: Convergences curve of 100 independent trials of case study 2

From Figure 7, it can be seen that the variation range of the total cost value of the best ED result obtained from each independent simulation is relatively small and all these total cost values are equally distributed between the minimum and the maximum total cost values without any bias, thus demonstrating the robustness of the proposed algorithm for solving the ED problem.

## CONCLUSION

This paper proposes a new reliable and efficient technique, ‘‘modified shuffle frog leaping algorithm or MSFLA”, for solving economic dispatch problem in power systems considering the valve-point effects. Obtained results are compared with other algorithms that addresses in literatures and it is found that MSFLA approach handles the problem of premature convergence found in other algorithms very effectively by generating mutant vectors. The effectiveness and robustness of the proposed method are examined to two case studies. On the basis of simulation results credibility and computation efficiency show the superiority of the MSFLA over other methods. The simulation results indicate that this optimization method is very accurate and converges very rapidly so that it can be used in the practical optimization problems.

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