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Multi Case Non-Convex Economic Dispatch Problem Solving by Implementation of Multi-Operator Imperialist Competitive Algorithm

Hamid Eghbalpour* and Mohammadreza Nabatirad†

Abstract – Power system analysis, Non-Convex Economic Dispatch (NED) is considered as an open and demanding optimization problem. Despite the fact that realistic ED problems have non-convex cost functions with equality and inequality constraints, conventional search methods have not been able to effectively find the global answers. Considering the great potential of meta-heuristic optimization techniques, many researchers have started applying these techniques in order to solve NED problems. In this paper, a new and efficient approach is proposed based on imperialist competitive algorithm (ICA). The proposed algorithm which is named multi-operator ICA (MuICA) merges three operators with the original ICA in order to simultaneously avoid the premature convergence and achieve the global optimum answer. In this study, the proposed algorithm has been applied to different test systems and the results have been compared with other optimization methods, tending to study the performance of the MuICA. Simulation results are the confirmation of superior performance of MuICA in solving NED problems.

Keywords: Non-convex optimization, Economic dispatch, Meta-heuristic algorithms, Imperialist competitive algorithm

1. Introduction

Non-convex economic dispatch (NED) is one of the most important optimization problems of power systems which needs to be solved accurately. The main aim of the NED is to share power demand among the generators economically while satisfying all system constraints. The basic ED only considers the power balance constraint apart from the generating capacity limitations, while a realistic ED has to take prohibited operating zones, valve-point loading effects and multi-fuel options into account to provide the complementary ED formulation. Therefore, a practical ED is represented as a non-linear and non-convex optimization problem with equality and inequality constraints which needs a superior optimization algorithm to find the global solution.

Most often, traditional optimization methods [1-10] such as linear programming (LP), non-linear programming (NLP), power exchange algorithm, quadratic programming (QP), Newton method and Lambda iteration are used to solve NED problems. These methods require continuity, convexity and differentiability fto be applicable. They also usually involve heavy computations and result in a local solution rather than a global one. So, it is needed to use more efficient approaches to overcome the difficulty of NED problems.

Over the past decade, because of their great potential to find optimal or close-to-optimal solutions, meta-heuristic optimization algorithms have attracted significant attention to solve NED problems. They are suitable choices for solving NED problems owing to their global search power as well as constraint handling capacity. These techniques can be addressed by genetic algorithm (GA) [11], particle swarm optimization (PSO) [12], differential evolution (DE) [13], tabu search (TS) [14], pattern search (PS) [15], bacterial foraging (BF) [16], evolutionary programming (EP) [17], simulated annealing (SA) [18], evolutionary strategy optimization (ESO) [19] and hybridization of them [20-24].

This paper proposes a novel meta-heuristic optimization technique based on imperialist competitive algorithm (ICA) including new case studies. ICA is a recently developed stochastic optimization method inspired by human's socio-political evolution [25]. The basis of ICA originates from the attempt of the real world countries to extend their power over the other countries for using their resources and strengthen their own government. Imperialist countries try to dictate their power over the other countries and turn them into their colonies. They also compete with each other to take the ownership of the other countries. During this process, stronger empires will get more power and weaker ones will eventually collapse. ICA contains a population of countries and attempts to metaphorically mimic this process to find the optimum solution. Recently, the great performance of ICA in both convergence rate and obtaining global solution has led to its application in optimization problems in different areas [26-28]. To

† Corresponding Author: Dept. of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran. (mr.nabatirad@gmail.com)
* Dept. of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran. (h.eghbalpour.1987@ieee.org)
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enhance the capability of ICA in global optimization some improvements have been made in the literature. Combination of ICA with chaotic movement has been presented in [26]. In [27] authors have defined two movement steps to improve the performance of ICA. A modified ICA (MICA) has been proposed in [28] by introducing a new mutation operator to help the algorithm avoid premature convergence.

In this paper, to increase the global search power of ICA, a multi-operator ICA (MuICA) is proposed. MuICA attempts to avoid premature convergence by maintaining the population diversity. It takes the three operators simultaneously into account, namely, chaos, mutation and repulsion factor. These operators increase the probability of providing a good balance between exploration and exploitation and discovering the global solution.

The proposed technique is used to solve three types of NED problem, namely, NED with prohibited operating zones, NED with valve-point loading effects, and NED with both valve-point loading effects and multi-fuel options. In order to study the effectiveness of MuICA, its performance is compared with the results reported in the literature obtained by the other techniques.

The rest of this paper is arranged as follows: Section 2 provides formulation of NED problem; In Section 3, ICA and the proposed MuICA are explained in detail; Simulation results and discussions are given in Section 4 and finally, conclusion is presented is Section 5.

2. Formulation of Non-convex Economic Dispatch

NED is defined as an optimization problem with the aim of minimizing total cost function by finding the optimal combination of power generations while satisfying various equality and inequality constraints. The NED problem is formulated as follows:

2.1. Cost function

The cost function of NED problem is defined by Eq. (1).

$$Min\, F(X) = \sum_{j=1}^{N_g} FC_j\left(P_{gj}\right) \tag{1}$$

where F is the total generation cost, $X = \left\lfloor P_{g1}, P_{g2}, \ldots, P_{gN_g} \right\rfloor$ denotes the decision variables vector, P_{gj} specifies the active generation of jth unit, FC_j is the fuel cost function of jth generator, and N_g denotes the number of generators.

In general, the fuel cost of thermal generation units is considered by a quadratic function as Eq. (2).

$$FC_j\left(P_{gj}\right) = a_j P_{gj}^2 + b_j P_{gj} + c_j \tag{2}$$

where a_j, b_j and c_j are cost coefficients for jth generator.

In multi-valve steam turbines the valve opening process produces a ripple-like effect in the heat rate curve of generators. By considering the valve-point loading effect, a sinusoidal term is incorporated in Eq. (2). Hence, Eq. (2) is modified and a more accurate cost function is defined by Eq. (3).

$$\begin{aligned} FC_j\left(P_{gj}\right) = {} & a_j P_{gj}^2 + b_j P_{gj} + c_j + \\ & \left| e_j \sin(f_j (P_{gj\min} - P_{gj})) \right| \end{aligned} \tag{3}$$

where e_j and f_j are non-smooth fuel cost coefficients and $P_{gj\,min}$ is the minimum power generation limit of jth generator.

In practice, there are many generating units which are supplied with multiple fuels. The cost function of such units should be considered with a few piecewise functions to reflect the effects of fuel type changes. As a result, the fuel cost function of jth unit considering both the valve-point loading and multiple fuel effects is defined by Eq. (4).

$$FC_j\left(P_{gj}\right) = \begin{cases} a_{j,1} P_{gj,1}^2 + b_{j,1} P_{gj,1} + c_{j,1} + \left| e_{j,1} \sin(f_{j,1} (P_{gj\min} - P_{gj})) \right| \\ \quad if\ P_{gj\min} \le P_{gj} \le P_{gj,1}\ ; \text{fuel type 1} \\ a_{j,2} P_{gj,2}^2 + b_{j,2} P_{gj,2} + c_{j,2} + \left| e_{j,2} \sin(f_{j,2} (P_{gj\min} - P_{gj})) \right| \\ if\ P_{gj\min} \le P_{gj} \le P_{gj,2}\ ; \text{fuel type 2} \\ \quad \cdots \\ a_{j,t} P_{gj,t}^2 + b_{j,t} P_{gj,t} + c_{j,t} + \left| e_{j,t} \sin(f_{j,t} (P_{gj\min} - P_{gj})) \right| \\ if\ P_{gj\min} \le P_{gj} \le P_{gj,t}\ ; \text{fuel type t} \end{cases} \tag{4}$$

where $a_{j,t}$, $b_{j,t}$, $c_{j,t}$, $e_{j,t}$, and $f_{j,t}$ are the fuel cost coefficients of the jth generator for the tth fuel type.

2.2. Constraints

2.2.1. Power balance constraint

Real power balance is defined by Eq. (5).

$$\sum_{j=1}^{N_g} P_{gj} = P_D + P_L \tag{5}$$

where P_D is total power demand of consumers and P_L denotes the total losses of the transmission network.

Total transmission loss given by Eq. (6) is expressed with a quadratic function of generator power outputs and B-coefficients.

$$P_L = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{N_g} B_{0i} P_{gi} + B_{00} \tag{6}$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{0i} denotes ith element of the loss coefficient vector, and B_{00} is the loss coefficient constant.

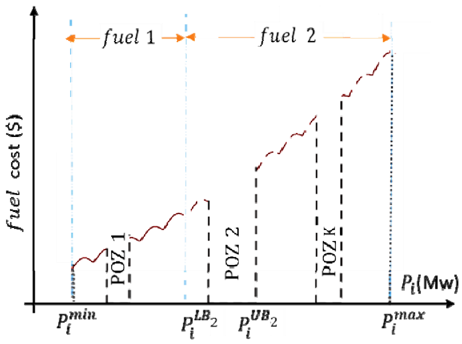

Fig. 1. Fuel Cost Curve with Considering Multi-Fuel and POZ

2.2.2. Power output constraints

Power operating limit is defined by Eq. (7).

$$P_{gj\min} \le P_{gj} \le P_{gj\max} \tag{7}$$

where $P_{gj\ min}$ and $P_{gj\ max}$ are the lower and upper allowable limit of power generation for jth generator, respectively.

2.2.3. Constraints of prohibited operating zones

Faults in the generating units or in the associated auxiliaries such as boilers and feed pumps may result in instability in certain ranges of the generator power output. These ranges are prohibited from operation and fuel cost function of generators with prohibited zones will be discontinuous. To avoid prohibited zones the following constraint must be regarded in NED problem.

$$P_{gj} \in \begin{cases} P_{gj}^{\min} \le P_{gj} \le P_{gj}^{LB_1} \\ P_{gj}^{UB_{k-1}} \le P_{gj} \le P_{gj}^{LB_k} \\ P_{gj}^{UB_k} \le P_{gj} \le P_{gj}^{\max} \end{cases} \quad j = 1,2,\ldots,N_g \tag{8}$$

Where $P_{gj}^{LB_k}$ and $P_{gj}^{UB_k}$ are the lower and upper bounds of the kth prohibited zone for jth unit and k denotes the prohibited zone's index.

Fig. 1 shows fuel Cost Curve with Considering Multiple Fuel and Prohibited operating zone.

3. Imperialist Competitive Algorithm

3.1. Original version of ICA

Originally proposed by Atashpaz and Lucas [25], ICA is a population-based meta-heuristic search technique. In ICA, each member of the population is called country and specified by a vector containing the problem variables. Some of the best countries are selected as imperialists and the other countries make the colonies of these imperialists. According to their power, all the colonies are distributed among the imperialists. An imperialist along with its colonies is named an empire.

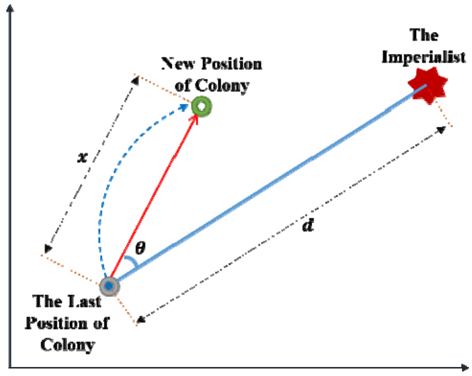

Fig. 2. Moving a colony towards the relevant imperialist

Based on the assimilation policy shown in Fig. 2, each colony moves towards the relevant imperialist by a deviation of θ from the connecting line between the colony and its imperialist by x units, where θ and x are random numbers with uniform distribution, $\beta > 1$ is usually a constant value, and d denotes the distance between the colony and the imperialist.

$$x \sim U(0, \beta \times d) \tag{9}$$

$$\theta \sim U(-\gamma, \gamma) \tag{10}$$

where γ is a parameter that adjusts the deviation from the original direction.

In order to escape local optima, ICA makes use of revolution operator. This operator randomly selects some countries and replaces them with new random positions. As a colony moves towards an imperialist, there is the possibility that the colony reaches to a position with better quality than that of the imperialist. In this case, the imperialist and the colony change their positions and the algorithm will be continued using this new country as the imperialist.

The most important process of ICA is the imperialistic competition in which all the empires attempt to take the possession of the colonies of the other empires and control them. Through the imperialistic competition the power of the weaker empires will decrease and consequently the power of more powerful ones will increase. This process is modelled by just picking one of the weakest colonies of the weakest empires and making a competition among all the empires to possess this colony. In this competition, based on its total power, each empire has the probability of taking the possession of the colony. The total power of an empire defined by Eq. (11) is the sum of the imperialist power and an arbitrary percentage of the mean power of its colonies.

$$T.C_n = \cos t(imperialist_n) + \zeta \times mean\{\cos t(colonies\ of\ empire_n)\} \tag{11}$$

where $T.C_n$ is the total power of the nth empire and ξ is a positive number.

During the imperialistic competition, powerless empires collapse in the imperialistic competition and the corresponding colonies will be divided among the other empires.

Moving colonies toward imperialists are continued and imperialistic competition and implementations are performed during the search process. When the number of iterations reaches to a pre-defined value, the search process is stopped.

3.2 Multi-operator imperialist competitive algorithm (MuICA)

Like other meta-heuristic algorithms, ICA suffers from premature convergence. Most often, premature convergence is the result of losing diversity. To conquer the problem of premature convergence and obtain more optimistic results, we introduce MuICA by applying three operators simultaneously, namely, repulsion factor, chaos and mutation.

3.2.1. Repulsion factor

Repulsion technique ensures that all the colonies of an empire will not move towards the related imperialist. By considering this operator, a part of colonies are encouraged to move in opposite direction of the imperialist. Hence, there is more chance to keep the diversity of the population and find new positions of the search space with better quality. With respect to the repulsion factor, the updating pattern of each colony is modified as follows:

$$\begin{aligned} X_{new} &= X_{old} + sign(f) \times \\ &\left[rand \times \beta \times (X_{imp} - X_{old}) \right] \end{aligned} \tag{12}$$

$$sign(f) = \begin{cases} 1 & if \quad f \le p_f \\ -1 & if \quad f \ge p_f \end{cases} \tag{13}$$

Where f is a uniformly distributed number between 0 and 1 and P_f is a predefined probability, controlling the repulsion rate.

3.2.2. Chaos

Chaos has some good properties such as stochastic properties, and regularity. A chaotic sequence can go through every state in a certain area according to its own regularity, and every state is experienced only once. By using a chaotic movement an optimization algorithm can escape local optima more easily. In ICA the parameter of β is a constant value that is set at the beginning of the algorithm. Due to the fact that this parameter affects the algorithm's performance, we use a chaotic sequence to produce this parameter. Logistic function defined by Eq. (14) is a well-known method to produce a chaotic sequence where the initial value of β is a random number between 0 and 1 (not the points of 0.25, 0.50 and 0.75).

$$\beta^{t+1} = 4\beta^t (1 - \beta^t) \tag{14}$$

3.2.3. Mutation factor

As a powerful strategy, mutation diversifies the ICA population and improves its performance by preventing premature convergence to local optima. A new mutation factor has been introduced and validated in [28]. To apply this mutation factor after generating a new candidate solution by moving a colony towards the relevant imperialist, three colonies are selected randomly and another candidate solution is produced. A comparison is made between the two new candidate solutions and the better one is chosen as the new position of the colony. More explanation about this approach can be found in [28].

4. Simulation Results

In order to study the efficiency of the proposed algorithm in solving NED problems, four case studies are considered here. The proposed algorithm is coded and executed in MATLAB environment. Owing to the stochastic nature of the proposed algorithm, 50 independent runs are carried out and the minimum, mean and maximum costs of the system over these runs are reported. The parameter setting of the ICA-based algorithms is as follows: the population size is set to 100 of which eight countries with the best quality are selected as imperialists; the value of ξ, β, γ, P_f and revolutionary rate are selected 0.01, 3.2, 0.02, 0.9 and 0.03, respectively. It is worthwhile to mention that the parameter setting is based on trial and no attempt has made to optimize it.

4.1. Case study 1

The first test system includes 10 generators in which both valve-point loading effects and multi-fuel options are regarded. The system information can be found in [29]. The total load demand of this system is 2700 MW and transmission losses are neglected.

Table 1 lists three indexes, namely, the minimum, the mean and the maximum costs, found by MuICA over 50 runs in comparison with the results obtained by the other optimization techniques: ICA, CHBMO [30], IHBMO [30], HBMO [30], ARCGA [31], PSO-LRS [31], NPSO [31], NPSO-LRS [31], DSPSO-TSA [32], CCPSO [33], CBPSO-RVM [34], APSO [35], PSO [31], TSA [32], TS [36], RGA [31], DE [37], ED-DE [38], IGA-MU [31], ACO [36], CGA-MU [31] and GA [32].

As can be seen, the best performance belongs to the proposed MuICA, because it has found the minimal indexes. The low difference between the indexes indicates the robustness of the proposed algorithm. MuICA not only outperforms the original ICA but also produces better results than the other algorithms recently reported in the literature. The performance of MuICA will be more prominent if we consider that the maximum cost found by this algorithm is smaller than the minimum costs found by all the other ones except IHBMO. The optimum dispatch result related to the best performance of MuICA is shown in Table 2.

Table 1. Comparison between the performance of the proposed algorithm and the other ones on case study 1 with load demand of 2700 MW

Algorithm	Minimum cost ($/h)	Mean cost $/h)	Maximum cost ($/h)
MuICA	623.7199	623.7515	623.7956
ICA	624.1249	624.4861	625.4423
CHBMO	623.8905	623.9876	624.0748
IHBMO	623.7620	623.8263	623.9586
HBMO	624.2547	624.3962	624.4829
ARCGA	623.8281	623.8431	623.8550
PSO-LRS	624.2297	625.7887	628.3214
NPSO	624.1624	624.9985	627.4237
NPSO-LRS	624.1273	624.9985	626.9981
DSPSO–TSA	623.8375	623.8625	623.9001
CCPSO	623.8266	623.8273	623.8291
CBPSO-RVM	623.9588	624.0816	624.2930
APSO	624.0145	624.8185	627.3049
PSO	624.3045	624.5054	625.9252
TSA	624.3078	635.0623	624.8285
TS	624.0100	624.5100	624.9600
RGA	624.5079	624.5081	624.5088
DE	624.5146	624.5246	624.5458
ED-DE	623.8790	623.8807	623.8894
IGA-MU	624.5178	625.8692	630.8705
ACO	623.9000	624.3500	624.7800
CGA-MU	624.7193	627.6087	633.8652
GA	624.5050	624.8169	624.7419

Table 2. Optimal NED found by MuICA for case study 1 with load demand of 2700 MW

Generator	Output power (MW)	Fuel type
1	218.1049865	2
2	212.1547035	1
3	280.65706363	1
4	238.745780914	3
5	279.80611185	1
6	239.52658465	3
7	290.09837831	1
8	239.68637751	3
9	425.3516652	3
10	275.86834775	1
	Total cost ($/h)	623.7199

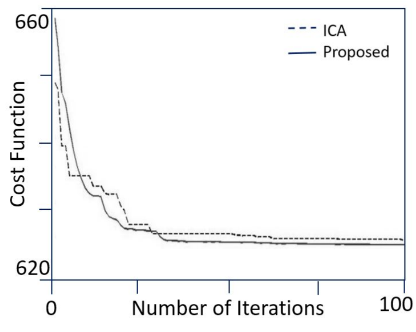

Fig. 3. Convergence process of MuICA in solving case study 1 with the load demand of 2700 MW

In order to observe the convergence rate of MuICA, the best value of the cost function during the iterations is plotted. Fig. 3 illustrates a comparison between the convergence rate of ICA and MuICA. It is clear that MuICA discovers the promising region of the search space quickly and leads to the optimum solution

As another investigation, the influence of the load demand is studied on the algorithm's performance. So, this system is also solved with the total demand of 2400, 2500 and 2600 MWs. Table 3 summarizes the performance of the proposed algorithm in comparison with the results obtained by ICA, CIHBMO [30], CMSFLA [39], DE [37], RGA [31], PSO [31] and ARCGA [31]. It is clear that MuICA yields better results than the other algorithms in all cases. The optimum dispatch along with the cost function related to the best performance of MuICA is given in Table 4.

4.2. Case study 2

This test system consists of 13 thermal units with valve-point loading effects. The total load demand of 2520 MW should be economically satisfied by these generators. System information can be found in [17]. Table 5 represents the comparison between the performance of

Table 3. Comparison between the performance of the proposed algorithm and the other ones on case study 1 with different load demands

Algorithm	Total generation cost ($/h)		
	Pload = 2400 MW	Pload = 2500 MW	Pload = 2600 MW
MuICA	481.642	526.156	574.2808
ICA	482.236	526.918	575.1022
CIHBMO	481.735	526.246	574.3925
CMSFLA	481.735	526.246	574.3925
DE	482.511	527.018	575.1610
RGA	482.527	527.036	575.1753
PSO	482.508	527.018	575.1606
ARCGA	481.743	526.258	574.4054

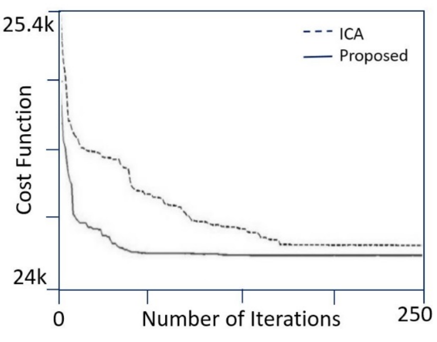

Fig. 4. Convergence process of MuICA on case study 2

Table 4. Optimum dispatch found by MuICA for case study 1 with different loads

Generator	Pload = 2400 MW		Pload = 2500 MW		Pload = 2600 MW	
	Output power (MW)	Fuel type	Output power (MW)	Fuel type	Output power (MW)	Fuel type
1	189.30815	1	205.781042	2	216.05097	2
2	201.75699	1	206.21317	1	210.66933	1
3	253.83858	1	264.92936	1	277.531608	1
4	232.564717	3	237.26770	3	238.342668	3
5	240.693627	1	258.36436	1	276.31395	1
6	233.345521	3	235.898574	3	239.257842	3
7	254.53342	1	268.764448	1	285.357138	1
8	232.43034	3	235.789642	3	239.014522	3
9	320.433103	1	333.165538	1	344.790829	3
10	241.09551	1	253.826151	1	272.671128	1
Total cost ($/h)	481.64263		526.15646		574.28083	

Table 5. Comparison between the performance of MuICA and the other algorithms on case study 2

Algorithm	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)
MuICA	24169.917	24169.91	24169.91
ICA	24203.447	24221.45	24216.68
FAPSO-NM	24169.92	24170.00	24170.50
FAPSO	24170.93	24173.00	24176.40
PSO	24262.73	24271.92	24277.81
GA-SA	24275.71	-	-
HGA	24169.92	-	-
ESO	24179.59	-	-
EP-PSO	24266.44	-	-
PSO-SQR	24261.05	-	-
DE	24169.91	-	-
GA	24398.23	-	-
SA	24970.91	-	-

Table 6. Optimum dispatch found by MuICA for case study 2

Generator	Output power (MW)
1	628.318530
2	299.199300
3	299.1993003
4	159.7331001
5	159.7331001
6	159.7331001
7	159.7331001
8	159.7331001
9	159.7331001
10	77.3999125
11	77.3999125
12	92.3999125
13	87.6845303
Total cost ($/h)	24169.7196

MuICA and ICA, FAPSO-NM [40], FAPSO [40], PSO [40], GA-SA [18, 20], HGA [20], ESO [19], EP-PSO [20, 41], PSO-SQR [42], DE [13], GA [11, 20] and SA [18, 20] on this test system. MuICA produces better results than the other algorithms. However, the performance of FAPSO-NM, HGA and DE in terms of the minimum cost is slightly higher than that of MuICA. Table 6 shows the optimum dispatch found by MuICA. The convergence process of the ICA-based algorithms is illustrated in Fig. 4.

Table 7. Comparison between the proposed algorithm and the other ones on case study 3

Algorithm	Mean cost	Minimum cost	Maximum
MuICA	31757.01	31727.973	31821.95599
ICA	31990.42	31940.63	32057.48
CIHBMO	32548.58	32548.58	32548.58
CHBMO	32571.44	32555.70	32589.76
IHBMO	32552.89	32552.46	32554.66
HBMO	32663.19	32637.62	32676.07
SPSO	-	32798.69	-
PC-PSO	-	32775.36	-
DE	32609.85	32588.86	32641.41
SOH-PSO	32878	32751.39	32945
PSO	32989	32858	33031
MTS	32767.4	32716.87	32796.13
SCA	33138.30	32867.02	33381.06
APSO	32679.87	32742.77	-
CSO	-	32588.91	32796.77
CPSO	33021	32834	33318
ESO	32620	32640.86	32710
BF	32796.8	32784.5	-
MDE	32708.1	32704.9	32711.5
TSA	33066.76	32917.87	33245.54
DSPSO-TSA	32724.63	32715.06	32730.39
GA	33228	33063.54	33337
SA	32869.51	32786.4	33028.95

4.3. Case study 3

The third test system has 15 units of which four units include prohibited zones. In this system, the load demand is 2630 MW and transmission losses are considered. The system information can be found in [37]. Table 7 summarizes the performance of MuICA in comparison with ICA, CIHBMO [30], CHBMO [30], IHBMO [30], HBMO [30], SPSO [43], PC-PSO [16], DE [42], SOH-PSO [43,44], PSO [44], MTS [45], SCA [46], APSO [47], CSO [46], CPSO [44], ESO [48], BF [44], MDE [44], TSA [45], DSPSO-TSA [45],GA [44] and SA[46] . It is clear that MuICA yields better results than the other algorithms. In this system, after MuICA, ICA outperforms the performance of the other algorithms reported in the literature. Table 8

Table 8. Optimum dispatch found by MuICA for case study 3

Generator	Output power (MW)
1	454.9065
2	455
3	130
4	130
5	218.0829
6	460
7	465
8	60
9	25.08434
10	44.23427
11	78.6956
12	80
13	25.01564
14	15
15	15
Ploss (MW)	26.01938
Total cost ($/h)	31727.97377

Table 9. Comparison between the proposed algorithm and the other ones on case study 4

Algorithm	Minimum cost	Mean cost ($/h)	Maximum cost
MuICA	121430.451026	121640.28086	121846.04544
ICA	122297.90	122625.46	123174.96
CASO	121865.63	122100.74	-
HBMO	121639.38	121851.7724	121939.742
CHBMO	121639.38	121851.77	121939.74
IHBMO	121517.8	121589.18	121711.85
FAPSO	121712.4	121778.246	121873.17
MPSO	122252.27	-	-
DEC-SQP	122174.16	122295.13	-
PSO-SQP	122094.67	122295.13	-
FCASO	121516.47	122082.59	-
BBO	121479.5	-	-
SOH-PSO	121501.14	-	-
IFEP	122624.35	123382.00	125740.63
MFEP	122647.57	123489.47	-
PAA	122243.18	122243.189	122243.189
ESO	122122.16	122558.45	123143.07
PSO-LRS	122035.79	122558.4565	123461.679
IGA	121915.93	122811.41	123334.00
GA	121819.25	-	-
PSO	122513.91	122513.9175	123467.408
NPSO	121704.73	122221.36	122995.09
ST-HDE	121698.51	122304.30	-
HDE	121698.51	122304.30	-
EP-SQP	122323.97	122379.63	-
PSO-GM	121845.98	122398.38	123219.22
TS	122288.38	122590.89	122424.81
ACO	121811.37	122048.06	121930.58
NPSO-LRS	121664.4308	122209.3185	122981.591
APSO	121663.52	122153.67	122912.39
SOH-PSO	121501.14	121853.57	122446.30
CSO	121461.67	121936.19	122844.53

indicates the optimum dispatch along with the transmission losses found by MuICA.

4.4. Case study 4

This system includes 40 units with valve-point loading effects. The load demand is 10500 MW and the system information is obtainable from [17]. Because of high dimension, this problem is challenging and it is difficult to obtain the global optimum. The performance of MuICA in comparison with ICA, CASO [49], HBMO [30], CHBMO [30], IHBMO [30], FAPSO [40], MPSO [20,13], DEC-SQP [20,13], PSO-SQP [20,13], FCASO [49], BBO [50], SOH-PSO [44], IFEP [17], MFEP [17], PAA [52], ESO [19], PSO-LRS [31], IGA [51], GA [44], PSO [44], NPSO [24], ST-HDE [43], HDE [20,13], EP-SQP [46,48], PSO-GM [53], TS [36], ACO [36], NPSO-LRS [31], APSO [31], SOH-PSO [43] and CSO [46] in terms of minimum, mean and maximum costs has been listed in Table 9. Like the previous test systems, the performance of MuICA in this system is superior. Table 10 represents the optimum dispatch for this system found by MuICA algorithm.

Table 10. Optimum dispatch found by MuICA for case study 4

Gen.	Output power (MW)	Gen.	Output power (MW)
1	111.474243	21	523.2879421
2	113.4804037	22	523.2920375
3	97.4541575	23	523.430238
4	179.744369	24	523.4606948
5	90.21042717	25	523.280222
6	140	26	523.3220767
7	259.9753648	27	10
8	284.7037714	28	10
9	284.6787530	29	10
10	130	30	89.4185477
11	168.7997273	31	190
12	94	32	190
13	214.76120829	33	190
14	394.2817449	34	165.6479652
15	304.5209910	35	200
16	394.2793972	36	200
17	489.2882395	37	110
18	489.3048918	38	110
19	511.327569	39	110
20	511.2956400	40	511.2793738
Total cost ($/h)		121430.451026	

5. Conclusion

This paper proposes a novel version of imperialist competitive algorithm (ICA) named MuICA to tackle the complexity of NED problems by various case studies. MuICA makes use of the advantages of three operators simultaneously to keep the population diversity and avoid premature convergence. The potential of the proposed algorithm is studied by solving different NED problems. Simulation results reveal that MuICA not only produces better results than ICA but also outperforms the other methods proposed in the literature. As a result, promising performance of MuICA makes this technique a superior candidate to efficiently solve NED problems.

References

[1] AJ. Wood and BF. Wollenberg, "Power generation, operation and control," New York: John Wiley & Sons, 1994.

[2] H. Sadaat, "Power system analysis," WCB/McGraw-Hill; 1999.

[3] DW. Ross and S. Kim, "Dynamic economic dispatch of generation," *IEEE Trans Power Appar Syst,* vol. 99, no. 6, pp. 2060-2068, 1980.

[4] ZX. Liang and JD. Glover, "A zoom feature for a programming solution to economic dispatch including transmission losses," *IEEE Trans Power Syst,* vol. 7, no. 3, pp. 544-550, 1992.

[5] JY. Fan and L. Zhang, "Real-time economic dispatch with line flow and emission constraints using quadratic programming," *IEEE Trans Power Syst,* vol. 13, no. 2, pp. 320-325, 1998.

[6] H. Eghbalpour, MR. Nabatirad, Y. Rahnamafard, A. Pirayesh, "Power exchange algorithm for improving answers of meta-heuristic methods in Economic Dispatch," *Indian Journal of Science and Technology,* vol. 8, no. 17, pp. 1-8, August 2015.

[7] AJ Rabin, AH. Coonick and BJ Coory, "A homogeneous linear programming algorithm for the security constrained economic dispatch problem," *IEEE Trans Power Syst,* vol. 15, no. 3, pp. 930-936, 2000.

[8] CE. Lin and GL. Viviani, "Hierarchical economic dispatch for piecewise quadratic cost functions," *IEEE Trans Power Appar Syst*, vol. 103, no. 6, pp. 1170-1175, 1984.

[9] SD. Chen and JF. Chen, "A direct Newton-Raphson economic emission dispatch," *Electr Power Energy Syst,* vol. 25, pp. 411-417, 2003.

[10] HT. Yang and SL. Chen, "Incorporating a multi-criteria decision procedure into the combined dynamic programming/production simulation algorithm for generation expansion planning," *IEEE Trans Power Syst,* vol. 4, no. 1, pp. 165-175, 1989.

[11] DC. Walters and GB. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading," *Power Systems, IEEE Transactions on.,* vol. 8, pp. 1325-1332, 1993.

[12] JB. Park, K-S. Lee, J-R. Shin and KY. Lee, "A particle swarm optimization for economic dispatch with non-smooth cost functions," *IEEE Trans Power Syst,* vol. 20, no. 1, pp. 34-42, 2005.

[13] P. Subbaraj, R. Rengaraj and S. Salivahanan, "Enhancement of combined heat and power economic dispatch using self-adaptive real-coded genetic algorithm," *Appl Energy,* vol. 86, no. 6, pp. 915-921, 2009.

[14] VM. Lin, FS. Cheng and MT. Tsay, "An improved tabu search for economic dispatch with multiple minima," *IEEE Trans Power Syst,* vol. 17, no. 1, pp. 108-112, 2002.

[15] J. Al-Sumait, A. Al-Othman and J. Sykulski, "Application of pattern search method to power system valve-point economic load dispatch," *International Journal of Electrical Power & Energy Systems,* vol. 29, pp. 720-730, 2007.

[16] B. Panigrahi and VR. Pandi, "Bacterial foraging optimisation: Nelder-Mead hybrid algorithm for economic load dispatch," *Generation, Transmission & Distribution, IET ,* vol. 2, pp. 556-565, 2008.

[17] N. Sinha, R. Chakrabarti and PK. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Trans Evol Comput,* vol. 7, no.1, pp. 83-94, 2003.

[18] KP. Wong and YW. Wong, "Genetic and genetic/ simulated-annealing approaches to economic dispatch," *IEE Proc Gen Transm Distrib,* vol. 141, no. 5, pp. 507-513, 1994.

[19] AP. Neto, C. Unsihuay and OR. Saavedra, "Efficient evolutionary strategy optimization procedure to solve the non-convex economic dispatch problem with generator constraints," *IEE Proc Gen Transm Distrib,* vol. 152, no. 5, pp. 653-660, 2005.

[20] DK. He, FL. Wang and Mao ZZ, "Hybrid genetic algorithm for economic dispatch with valve-point effect," *Electr Power Syst Res,* vol. 78, no. 4, pp. 626-363, 2008.

[21] K. Ashwani and G. Wenzhong, "Pattern of secure bilateral transactions ensuring power economic dispatch in hybrid electricity markets," *Appl Energy*, vol. 86, no. 7, pp. 1000-1010, 2009.

[22] L. Dos, S. Coelho and VC. Mariani, "Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect," *IEEE Trans Power Syst,* vol. 21. No. 2, pp. 989-996, 2006.

[23] T. Niknam, A. Khodaei and F. Fallahi "A new decomposition approach for the thermal unit commitment problem," *Appl Energy*, vol. 86, no. 9, pp. 1667-1674, 2009.

[24] AI. Selvakumar and T. Khanushkodi, "A new particle swarm optimization solution to non-convex economic dispatch problems," *IEEE Trans Power Syst,* vol. 22, no. 1, pp. 42-51, 2007.

[25] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition," City, 2007.

[26] S. Talatahari, B. Farahmand Azar, R. Sheikholeslami and A.H. "Gandomi, Imperialist competitive algorithm combined with chaos for global optimization," *Commun Nonlinear Sci Numer Simulat,* vol. 17, pp. 1312-1319, 2012.

[27] A. Kaveh and S. Talatahari, "Optimum design of skeletal structures using imperialist competitive algorithm," *Comput Struct,* vol. 88, pp. 1220-1229, 2010.

[28] T. Niknam, E. TaherianFard, N. Pourjafarian and A.

Rousta, "An efficient hybrid algorithm based on modified imperialist competitive algorithm and K-means for data clustering," *Engineering Applications of Artificial Intelligence,* vol. 24, pp. 306-317, 2012.

[29] CL. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *Power Systems, IEEE Transactions on.* , vol. 20, pp. 1690-1699, 2005.

[30] T. Niknam. HD. Mojarrad, HZ. Meymand and BB. Firouzi, "A new honey bee mating optimization algorithm for non-smooth economic dispatch," *Energy*, vol. 36, pp. 896-908, 2011.

[31] N. Amjady and H. Nasiri-Rad, "Solution of non-convex and non-smooth economic dispatch by a new Adaptive Real Coded Genetic Algorithm," *Expert Systems with Applications*, vol. 37, pp. 5239-5245, 2010.

[32] S. Khamsawang and S. Jiriwibhakorn "DSPSO-TSA for economic dispatch problem with non-smooth and non-continuous cost functions," *Energy Conversion and Management*, vol. 51, pp. 365-375, 2010.

[33] JB. Park, YW. Jeong, JR. Shin and KY. Lee, "An improved particle swarm optimization for non-convex economic dispatch problems," Power Systems, *IEEE Transactions on.* , vol. 25, pp. 156-166, 2010.

[34] H. Lu, P. Sriyanyong, YH. Song and T. Dillon, "Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function," *International Journal of Electrical Power & Energy Systems*, vol. 32, pp. 921-935, 2010.

[35] AI. Selvakumar and K. Thanushkodi, "Anti-predatory particle swarm optimization: solution to non-convex economic dispatch problems," *Electric Power Systems Research*. vol. 78, pp. 2-10, 2008.

[36] S. Pothiya, I. Ngamroo and W. Kongprawechnon, "Ant colony optimization for economic dispatch problem with non-smooth cost functions," *International Journal of Electrical Power & Energy Systems*, vol. 32, pp. 478-487, 2010.

[37] P. Manoharan, P. Kannan, S. Baskar and M. Iruthayarajan, "Penalty parameter-less constraint handling scheme based evolutionary algorithm solutions to economic dispatch," *Generation, Transmission & Distribution, IET,* vol. 2, pp. 478-490, 2008.

[38] Y. Wang, B. Li and T. Weise, "Estimation of distribution and differential evolution cooperation for large scale economic load dispatch optimization of power systems," *Information Sciences*, vol. 180, pp. 2405-2420, 2010.

[39] T. Niknam, BB. Firouzi and HD. Mojarrad, "A new evolutionary algorithm for non-linear economic dispatch," *Expert Systems with Applications*, vol. 38, pp. 13301-13309, 2011.

[40] T. Niknam, "A new fuzzy adaptive hybrid particle swarm optimization algorithm for non-linear, non-smooth and non-convex economic dispatch problem," *Applied Energy*, vol. 87, pp. 327-339, 2010.

[41] K. Swarup and PR. Kumar, "A new evolutionary computation technique for economic dispatch with security constraints," *International Journal of Electrical Power & Energy Systems*, vol. 28, pp. 273-283, 2006.

[42] T. Victoire and AE. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electric Power Systems Research*, vol. 71, pp. 51-59, 2004.

[43] KT, Chaturvedi, M, Pandit and L. Srivastava, "Self-organizing hierarchical particle swarm optimization for non-convex economic dispatch," Power Systems, *IEEE Transactions on*, vol. 23, pp. 1079-1087, 2008.

[44] N. Amjady, H. Sharifzadeh, "Solution of non-convex economic dispatch problem considering valve loading effect by a new Modified Differential Evolution algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 32, pp. 893-903, 2010.

[45] S. Khamsawang, S. Jiriwibhakorn, "DSPSO-TSA for economic dispatch problem with non-smooth and noncontinuous cost functions," *Energy Conversion and Management*, vol. 51, pp. 365-375, 2010.

[46] AI. Selvakumar, K. Thanushkodi, "Optimization using civilized swarm: solution to economic dispatch with multiple minima," *Electric Power Systems Research*, vol. 79, pp. 8-16, 2009.

[47] B. Panigrahi, V. Ravikumar Pandi and S. Das, "Adaptive particle swarm optimization approach for static and dynamic economic load dispatch," *Energy Conversion and Management*, vol. 49, pp. 1407-1415, 2008.

[48] N. Noman and H. Iba, "Differential evolution for economic load dispatch problems," *Electric Power Systems Research*, vol. 78, pp. 1322-1331, 2008.

[49] J. Cai, Q. Li, L. Li, H. Peng and Y. Yang, "A fuzzy adaptive chaotic ant swarm optimization for economic dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 34, pp. 154-160, 2012.

[50] A. Bhattacharya and P. Chattopadhyay, "Solving complex economic load dispatch problems using biogeography-based optimization," *Expert Systems with Applications*, vol. 37, pp. 3605-3615, 2010.

[51] S. Ling and FHF. Leung, "An improved genetic algorithm with average-bound crossover and wavelet mutation operations," *Soft Computing-A Fusion of Foundations, Methodologies and Applications*, vol. 11, pp. 7-31, 2007.

[52] WM. Lin, HJ. Gow, MT. Tsay, "A partition approach algorithm for non-convex economic dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 29, pp. 432-438, 2007.

[53] H. Lu, P. Sriyanyong, YH. Song and T. Dillon, "Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function," *International Journal of Electrical Power & Energy Systems*, vol. 32, pp. 921-395, 2010.

Hamid Eghbalpour was born in Iran, in 1987. He received the B.Sc. degree from Semnan University, Semnan, Iran in 2010 and the M.Sc. degree from Shahid Beheshti University, Tehran, Iran in 2012 both in electrical engineering - power. Currently He is a research assistant at Shahid Beheshti University and Also lecturer at Azad University of Khoramshahr and Arvandan Institute of Higher Education. His professions include presenting Industrial Courses regarding Control and Power issues in Oil and Gas Industry in the Middle East. His Research Interests are Power System Operation, Renewable Energy Systems, Smart Grids, Artificial Neural Network, Fuzzy Control and Optimization with Metaheuristics. He is a member of Iranian Wind Power, Renewable Energy and Fuzzy System Associations.

Mohammadreza Nabatirad was born in Tehran, Iran, in 1987. He received the B.Sc. degree from Isfahan University of Technology, Isfahan, Iran in 2010 and the M.Sc. degree from Shahid Beheshti University, Tehran, Iran in 2012, both in Electrical Engineering - Power. Currently he is pursuing the Ph.D. Degree with Monash University, Melbourne, Australia. His research interests are Power System Operation, Power System Dynamics, Distributed Generation, Renewable Energy Systems and Microgrids.