

A Multi-Operator Imperialist Competitive Algorithm for Solving Non-Convex Economic Dispatch Problem

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Abstract

Non-Convex Economic Dispatch (NED) has been addressed as an open and demanding optimization problem in power systems. Due to the fact that realistic ED problems have non-convex cost functions with equality and inequality constraints, conventional search methods are unable to effectively find the global solution. In recent years, because of their great potential to achieve optimal or close-to-optimal solution, meta-heuristic optimization techniques have attracted significant attention to tackle the complexity of NED problems. In this paper, an efficient approach is proposed based on Imperialist Competitive Algorithm (ICA). The proposed algorithm named multi-operator ICA (MuICA) merges the advantages of Repulsion factor, Chaos and Mutation factor operators to the original ICA to maintain the diversity and avoid premature convergence. In order to study the usefulness of the proposed algorithm, its performance is compared with those of the other methods on different test systems. Simulation results confirm the superior performance of MuICA in solving NED problems with different number of thermal units.

Keywords: Economic Dispatch, Imperialist Competitive Algorithm, Meta-Heuristic Algorithms, Non-Convex Optimization, Thermal Power Plants

1. Introduction

Non-Convex Economic Dispatch (NED) is one of the most important optimization problems of power system which needs to be solved effectively. The ultimate aim of the NED is to divide the power demand among the generators economically while satisfying various constraints. Though the basic ED only considers the power balance constraint apart from the generating capacity limitations, a realistic ED has to take prohibited operating zones, valve-point loading effects and multi-fuel options into account to provide the completeness for the 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 methods¹⁻¹⁰ such as Linear Programming (LP), Non-Linear Programming (NLP), Quadratic Programming (QP), Newton method and Lambda iteration are used to solve NED problems.

These methods that require continuity, convexity and differentiability conditions for being applicable, usually involve heavy computations, are local in nature and converge to a local solution rather than a global one. So, it is essential to use more efficient approaches to conquer 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 them²⁰⁻²⁴.

This paper proposes a novel meta-heuristic optimization technique based on Imperialist Competitive

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Algorithm (ICA). ICA is a recently developed stochastic optimization method inspired by human’s socio-political evolution²⁵. 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 to 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 to optimization problems in different areas²⁶⁻²⁸. To 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 in²⁶. In²⁷ authors have defined two movement steps to improve the performance of ICA. A Modified ICA (MICA) has been proposed in²⁸ by introducing a new mutation operator to help the algorithm for avoiding 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 advantages of three operators simultaneously into account, namely, chaos, mutation and repulsion factor. These operators increase the probability of the algorithm for 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.

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 Equation (1).

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

Where F is the total generation cost, $X = [P_{g1}, P_{g2}, \dots, P_{gN_g}]$ denotes the decision variables vector, P_{gj} specifies the active generation of j th unit, FC_j is the fuel cost function of j th 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 Equation (2).

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

Where a_j , b_j and c_j are cost coefficients for j th 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 Equation (2). Hence, Equation (2) is modified and a more accurate cost function is defined by Equation (3).

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

Where e_j and f_j are non-smooth fuel cost coefficients and $P_{gj\min}$ is the minimum power generation limit of j th 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 j th unit considering the valve-point loading and multiple fuel effects is defined by Equation (4).

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

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

2.2 Constraints

2.2.1 Power Balance Constraint

Real power balance is defined by Equation (5).

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

Where P_D is total load of consumers and P_L denotes the total losses of the transmission network.

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

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

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

2.2.2 Power Output Constraints

Power operating limit is defined by Equation (7).

$$P_{gjmin} \leq P_{gj} \leq P_{gjmax} \quad (7)$$

Where P_{gjmin} and P_{gjmax} are the lower and upper allowable limit of power generation for j th 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.

$$P_{gj} \in \begin{cases} P_{gj}^{\min} \leq P_{gj} \leq P_{gj}^{LB_1} \\ P_{gj}^{UB_{k-1}} \leq P_{gj} \leq P_{gj}^{LB_k} \\ P_{gj}^{UB_k} \leq P_{gj} \leq P_{gj}^{\max} \end{cases} \quad j=1,2,\dots,N_g \quad (8)$$

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

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

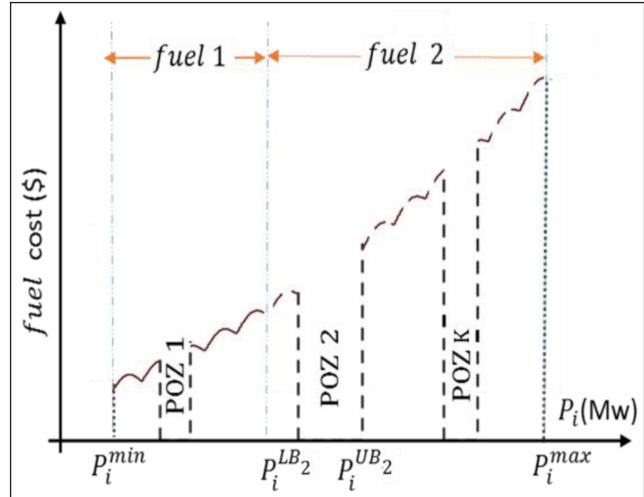


Figure 1. Fuel cost curve with considering multi-fuel and POZ.bn

3. Imperialist Competitive Algorithm

3.1 Original Version Of ICA

Originally proposed by²⁵, 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 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.

Based on the assimilation policy shown in Figure2, 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.

$$x \sim U(0, \beta \times d) \quad (9)$$

$$\theta \sim U(-\gamma, \gamma) \quad (10)$$

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

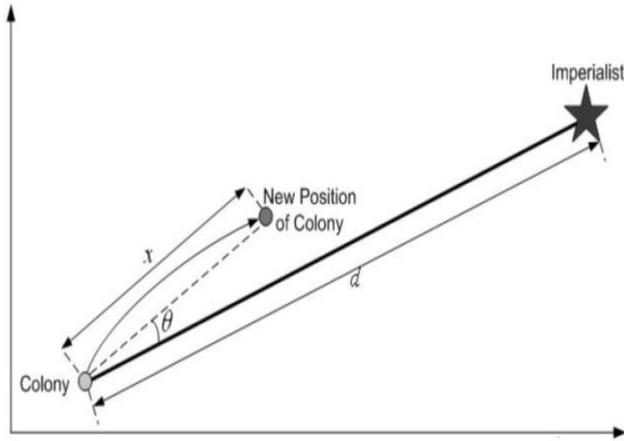


Figure 2. Moving a colony towards the relevant imperialist.

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 Equation (11) is the sum of the imperialist power and an arbitrary percentage of the mean power of its colonies.

$$T.C_n = \text{cost}(\text{imperialist}_n) + \xi \times \text{mean}\{\text{cost}(\text{colonies of empire}_n)\} \quad (11)$$

Where $T.C_n$ is the total power the n th 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 the diversity. To conquer the problem of premature convergence and obtain more optimistic results, we introduce MuICA by resorting simultaneously to three operators, 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:

$$X_{new} = X_{old} + \text{sign}(f) \times [\text{rand} \times \beta \times (X_{imp} - X_{old})] \quad (12)$$

$$\text{sign}(f) = \begin{cases} 1 & \text{if } f \leq p_f \\ -1 & \text{if } f \geq p_f \end{cases} \quad (13)$$

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 Equation (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).

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

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 in²⁸. To apply this mutation factor after generating a new candidate solution by moving a colony towards the relevant imperialist, three colonies are selected at random 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 in²⁸.

4. Results and Discussions

In order to study the efficiency of the proposed algorithm in solving NED problems, two 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 in²⁹. 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, CHBMO³⁰, IHBMO³⁰, HBMO³⁰, ARCGA³¹, PSO-LRS³¹, NPSO³¹, NPSO-LRS³¹, DSPSO-TSA³², CCPSO³³, CBPSO-RVM³⁴, APSO³⁵, PSO³¹, TSA³², TS³⁶, RGA³¹, DE³⁷, ED-DE³⁸, IGA-MU³¹, ACO³⁶, CGA-MU³¹ and GA³². 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

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

Maximum cost (\$/h)	Mean cost (\$/h)	Minimum cost (\$/h)	Algorithm
623.7956	623.7515	623.7199	MuICA
625.4423	624.4861	624.1249	ICA
624.0748	623.9876	623.8905	CHBMO
623.9586	623.8263	623.7620	IHBMO
624.4829	624.3962	624.2547	HBMO
623.8550	623.8431	623.8281	ARCGA
628.3214	625.7887	624.2297	PSO-LRS
627.4237	624.9985	624.1624	NPSO
626.9981	624.9985	624.1273	NPSO-LRS
623.9001	623.8625	623.8375	DSPSO-TSA
623.8291	623.8273	623.8266	CCPSO
624.2930	624.0816	623.9588	CBPSO-RVM
627.3049	624.8185	624.0145	APSO
625.9252	624.5054	624.3045	PSO
624.8285	635.0623	624.3078	TSA
624.96	624.51	624.01	TS
624.5088	624.5081	624.5079	RGA
624.5458	624.5246	624.5146	DE
623.8894	623.8807	623.8790	ED-DE
630.8705	625.8692	624.5178	IGA-MU
624.78	624.35	623.90	ACO
633.8652	627.6087	624.7193	CGA-MU
624.7419	624.8169	624.5050	GA

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.

In order to observe the convergence rate of MuICA, the best value of the cost function during the iterations is plotted. Figure 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 converges to the optimum solution.

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

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

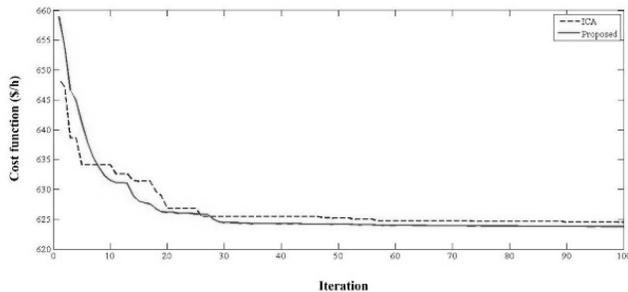


Figure 3. Convergence process of MuICA in solving case study 1 with the load demand of 2700 MW.

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 result obtained by ICA, CIHBMO³⁰, CMSFLA³⁹, DE³⁷, RGA³¹, PSO³¹ and ARCGA³¹. It is clear that MuICA yields better results than the other algorithms on all the 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 in¹⁷. Table 5 represents the comparison between the performance of MuICA

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	481.6426343	526.156468	574.28083
ICA	482.2362	526.9189	575.1022
CIHBMO	481.73574	526.24671	574.39252
CMSFLA	481.73574	526.24671	574.39252
DE	482.5114	527.0189	575.1610
RGA	482.5275	527.0360	575.1753
PSO	482.5088	527.0185	575.1606
ARCGA	481.7434	526.2589	574.4054

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

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	

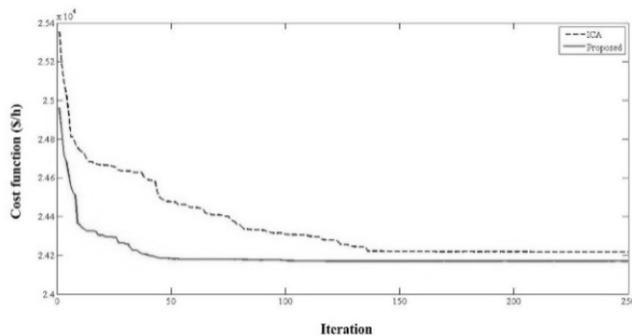
and ICA, FAPSO-NM⁴⁰, FAPSO⁴⁰, PSO⁴⁰, GA-SA^{18,20}, HGA²⁰, ESO¹⁹, EP-PSO^{20,41}, PSO-SQR⁴², DE¹³, GA^{11,20} and SA^{18,20} on this test system. MuICA produces better results than the other algorithms. However, the performance of FAPSO-NM, HGA and DE in terms of the minimum cost is slightly worse than that of MuICA. Table 6 shows the optimum dispatch found by MuICA. The convergence process of the ICA-based algorithms is illustrated in Figure 4.

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

Maximum cost (\$/h)	Mean cost (\$/h)	Minimum cost (\$/h)	Algorithm
24169.9177	24169.9177	24169.9176	MuICA
24216.6805	24221.4560	24203.4473	ICA
24170.5	24170.0017	24169.92	FAPSO-NM
24176.4	24173.0069	24170.93	FAPSO
24277.81	24271.9231	24262.73	PSO
-	-	24275.71	GA-SA
-	-	24169.92	HGA
-	-	24179.59	ESO
-	-	24266.44	EP-PSO
-	-	24261.05	PSO-SQR
-	-	24169.9177	DE
-	-	24398.23	GA
-	-	24970.91	SA

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

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

**Figure 4.** Convergence process of MuICA on case study 2.

5. Conclusion

This paper proposes a novel version of Imperialist Competitive Algorithm (ICA) named MuICA to tackle the complexity of NED problems. 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 as a superior candidate to efficiently solve NED problems.

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