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Research Article

A Modified Imperialist Competitive Algorithm for Combined Heat and Power Dispatch

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Abstract:
In this paper, a new approach based on Imperialist Competitive Algorithm (ICA) has been proposed to solve the combined heat and power economic dispatch (CHPED) problem. In order to avoid trapping in local optimum and improve the solution quality of the original ICA, a new assimilation policy has been addressed with varying coefficients during iterations. CHPED problem is a non-convex and nonlinear optimization problem which has various constraints. Unlike previous methods, valve point effects are considered in some case studies and the effect of valve-point in cost function is considered with adding an absolute sinusoidal term to conventional polynomial cost function. To evaluate the effectiveness of the proposed method, three different test cases with small, medium and large scales, which each case study contains different systems, have been applied to investigate the performance of the proposed method on the CHPED problems. Numerical results demonstrate the superiority of the proposed framework and reveal that MICA can find better solutions in comparison to the other methods.

Keywords: Assimilation Policy, Cogeneration, Combined Heat and Power; Imperialist Competitive Algorithm; Modified Imperialist Competitive Algorithm.

1- Introduction

Economic load dispatch (ELD) is one of the fundamental optimization problems in power system analysis. The purpose of ELD is to determine the optimal scheduling of power generations to match total power demand at minimal possible cost while satisfying the power generators and system constraints. The cost of generation, particularly in thermal power plants is excessive, hence, suitable planning of unit outputs can contribute to significant saving in operating cost. Over the years, a wide variety of optimization techniques [1-6] have been adapted to solve ELD problems, each of them has advantages and disadvantages. However, the growing trend of energy consumption in recent years has been the world's energy crisis and with rising fuel prices and environmental concerns of the electricity industry, the optimal utilization of multiple combined heat and power (CHP) units has been become a fundamental problem in Electric Power System. The purpose of combined heat and power, also known as the simultaneous production, is the concurrent production of electricity and useful heat. CHP is an efficient and reliable approach to generating power and thermal energy from a single fuel source. This can greatly increase the effectiveness and reduction of operational energy costs. CHP also contribute to global climate change by reducing greenhouse gas emissions. Complication arises if both of heat and power demands are required to meet simultaneously. The utility of cogeneration unit over conventional power generating unit and heat-only unit is that it satisfies both heat and electricity demands in an economical way. It makes the CHPED problem more complex than the conventional ELD problem. Conversion from fossil fuels and coal to electricity is a complicated process and most of the heat energy is wasted through this conversion process. For this reason, efficiency achieved by most of the conventional power plants is only about 50–60%. CHP unit reduce fuel and primary energy consumption without compromising the quality and reliability of the energy supply to consumers. The best CHP system can increase the efficiency up to 80% or more at the point of use. Moreover, significant reduction of environmental pollutants like CO_X, SO_X and NO_X can be achieved by CHP system. Consequently, it provides a cost-efficient means of generating low-carbon or renewable energies [7].

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Several optimization algorithms have been employed for solving the CHPED problems in recent two decades which can be divided into two main groups: mathematical approaches and metaheuristics. Non-linear optimization dual programming procedure that basically follows a two-level strategy [8], Lagrangian relaxation approach [9] and Branch-and-Bound algorithm [10] are considered as mathematical based methods which have been used to solve different CHPED problems. However, these algorithms are not able to solve discrete input and output modules, and/or non-convex characteristics of generator fuel to be used. In order to overcome the disadvantages of the above methods, a variety of techniques based on artificial intelligence have been proposed for solving CHP problems [11]. Generally, metaheuristics can optimize different problems without considering the complexity and constraints of the problem. Given that the CHPED problem is non-convex intrinsically, hence, the use of these methods seems reasonable.

Evolutionary Programming (EP) [12] was the first algorithm which has been developed for handling the CHPED problem in cogeneration systems. In this algorithm, new techniques for satisfying heat and power constraints has been suggested. A Genetic Algorithm (GA) based method entitled self-adaptive real-coded genetic algorithm (SARGA) has been proposed in [13] for solving CHPED problem. The proposed method uses a novel methodology to access constraints and has been tested on a simple cogeneration system and does not require any penalty parameters. Improved Genetic Algorithm (IGA) and IGA with multiplier updating (IGA-MU) [14] are other algorithms based on genetic algorithm which are proposed for solving CHPED. In the proposed IGA-MU method, it is assumed that the cost functions of heat generation plants and conventional power units are linear. In addition, recently, Haghrah et. Al. [15] have proposed a new version of real coded genetic algorithm with improved Mühlenbein mutation. The obtained results show that the suggested mutation is effective but unfortunately the selected test studies are partly small and the operation of this method on large-scale test systems has not been investigated. In Ref. [16] Harmony Search Algorithm (HSA) is proposed to handle the CHPED problem. In order to better evaluate the HS method, a new case study has been introduced. However, this framework has not regarded the valve-point effect in the formulation. Ant Colony Search Algorithm (ACSA) is another metaheuristic algorithm which has been proposed in [17] for solving the CHPED problem. Despite the acceptable ability search on small test systems, ACSA has some weaknesses such as premature convergence, access constraints and so on. Therefore, it has been proposed to improve the deficiencies of the algorithm by combining other methods. The first implementation of the cuckoo optimization algorithm for handling the complicated CHPED problem has been developed in [18]. Despite the acceptable results of this approach, the five-unit system is the largest case study which has been investigated by this approach and the capability of this method on large-scale test systems are not investigated. Mohammadi-Ivatloo *et al.* have developed time-varying acceleration coefficients particle swarm optimization (TVAC-PSO) [19] to solve the non-convex CHPED problems. In pursuance of conducting different constraints, appropriate penalty functions have been incorporated into objective function. In Ref. [20] a firefly algorithm is proposed to handle the reserve constrained combined heat and power dynamic economic emission dispatch problem. A noteworthy point of this work is that the ramp rate limits, valve-point effect, and spinning reserve requirements have been considered concurrently. Besides, enhanced simultaneous idea to fulfill the constraints has been presented in this work which biases the optimization towards the feasible region without imposing any limits on the objective function. Optimal planning including sitting and sizing of CHPs among arbitrary buses has been considered by Pazouki *et al.* in Ref. [21]. Ref. [22] can be used as a suitable survey for studies related to short-term scheduling of combined CHP. By and large, CHPED problem is a non-linear, non-convex, and non-smooth problem and each method not only must face these challenges but also find better optimal solution as global as possible in a reasonable time.

Recently, a state-of-the-art evolutionary algorithm inspired by social phenomena-human, has been proposed by Atashpaz *et al.*, named Imperialist Competitive Algorithm (ICA) [23]. This approach has been developed effectively to solve various real problems [24-26] and seems adaptable enough to improve its exploitation and exploration abilities. The algorithm is basically based on the empire framework, which supposes that stronger empires “imperialist” try to extend their power over the other weak countries “colony”. However, original ICA does not have effective performance in confronting with complex or large-scale optimization problems, and is likely to be trapped in the local optima. In addition, ICA has not been, to author's knowledge, used for solving economic dispatch of cogeneration systems. On account of all aforementioned reasons, a modified ICA (MICA) algorithm is proposed in this paper. In the proposed ICA, the effect of the most powerful empire is also considered in assimilation policy and this process is modeled by moving all the colonies toward the relevant imperialist and the most powerful empire. Additionally, to encourage the individuals to wander through the entire search space and enhancement of the global exploration ability, Time-Varying Coefficients (TVC) as the parameter automation strategy are proposed to incorporate in the assimilation concept. The effectiveness of the proposed strategy has been validated by numerous test cases. In accordance with the numerical results, MICA not only is able to solve various CHPED problems, but also provides economic benefits comparing to the other optimization approaches in an acceptable computational time.

This paper is organized as follows: First, the characteristics of CHP units are expressed and the CHPED problem is formulated by considering the valve point effects and losses. ICA algorithms are briefly presented in the next section and then the proposed algorithm is introduced. In the next section, how to apply the proposed algorithm on CHPED problem is described. Then the performance of the proposed approach on several systems is studied and the results of other methods are compared with the results of classical ICA algorithm as well as other approaches. Finally, the conclusion of the paper is outlined.

2. Mathematical Formulation of CHPED Problem

2.1. Objective Function

The system under consideration has power-only units, CHP units, and heat-only units. Fig. 1 shows the heat-power feasible operation region of a combined cycle cogeneration unit. The feasible operation region is enclosed by the boundary curve ABCDEF. Along the boundary curve BC, the heat capacity increases as the power generation decreases while the heat capacity decreases along the curve CD. The power output of the power units and the heat output of heat units are restricted by their own upper and lower limits. Usually the power capacity limits of cogeneration units are functions of the heat unit productions and the heat capacity limits are functions of the unit power generations [27].

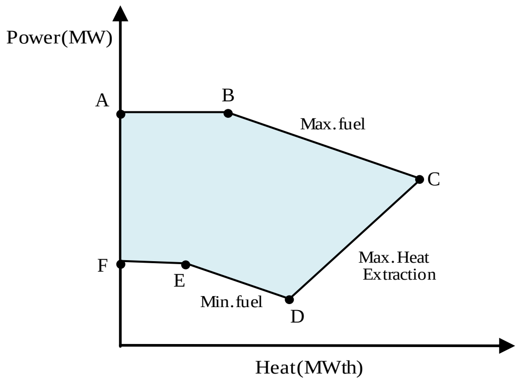

Fig (1): Feasible Operation Region for a Cogeneration Unit.

The CHP dispatch problem of a system is to determine the unit heat and power production so as to minimize the total production costs while satisfying various constraints. The mathematical model of the CHPED problem can be expressed as follows:

$$\min \sum_{i=1}^{N_p} C_i(P_i^p) + \sum_{j=1}^{N_c} C_j(P_j^c.H_j^c) + \sum_{k=1}^{N_h} C_k(H_k^h) \quad (\$/\text{h}) \tag{1}$$

where N_p, N_c and N_h are the number of conventional thermal units, cogeneration units and heat only units, respectively. $C_i(P_i^p)$, $C_j(P_j^c, H_j^c)$ and $C_k(H_k^h)$ are the fuel cost of conventional thermal unit *i*, the cost function of the cogeneration unit *j* and the cost of heat-only unit *k* for 1 h period. P and H are the heat and power output, respectively. The quadratic cost function of conventional units can be expressed as follows:

$$C_i(P_i^p) = \alpha_i(P_i^p)^2 + \beta_i P_i^p + \gamma_i \quad (\$/\text{h}) \tag{2}$$

where α_i, β_i and γ_i are the cost coefficients of the *i*th conventional thermal unit.

For a practical system, steam valve admission effects lead to the ripple in the production cost of generating unit. In order to model this effect more accurately, a sinusoidal term is added to the quadratic cost function [23]. Considering that the valve-point effect increases the non-smoothness and local optimal points of the solution space. So, the cost function with the valve-point effects can be represented as:

$$C_i(P_i^p) = \alpha_i(P_i^p)^2 + \beta_i P_i^p + \gamma_i + \left|\lambda_i \sin(\rho_i(P_i^{p\min} - P_i^p))\right| \quad (\$/\text{h}) \tag{3}$$

where λ_i and ρ_i are the are the coefficients of generator i reflecting valve-point effects.

The production cost of cogeneration and heat-only units are expressed as follows:

$$C_j(P_j^c.H_j^c) = a_j(P_j^c)^2 + b_jP_j^c + c_j + d_j(H_j^c)^2 + e_jH_j^c + f_jH_j^cP_j^c \quad (\$/\text{h}) \tag{4}$$

$$C_k(H_k^h) = a_k(H_k^h)^2 + b_kH_k^h + c_k \quad (\$/\text{h}) \tag{5}$$

where a_j, b_j, c_j, d_j, e_j and f_j are the cost coefficients of cogeneration units and a_k, b_k and c_k are the cost coefficients of the *k*th heat-only unit.

2.2. Constraints

The necessary equality and inequality constraints for minimizing the optimizing function (1) are represented as follows:

2.2.1. Equality Constrains

- **Power Production and Demand Balance Constraint**

$$\sum_{i=1}^{N_p} P_i^p + \sum_{j=1}^{N_c} P_j^c = P^{\text{demand}} \tag{6}$$

$$\sum_{j=1}^{N_c} H_j^c + \sum_{k=1}^{N_h} H_k^h = H^{\text{demand}} \tag{7}$$

P^{demand} and H^{demand} represent, respectively, the electric power and heat demand of the system.

2.2.1. Inequality Constrains

- **Capacity Limit Constraints**

$$P_i^{p\min} \le P_i^p \le P_i^{p\max} \qquad i = 1.\cdots.N_p \tag{8}$$

$$P_j^{c\min}(H_j^c) \le P_j^c \le P_j^{c\max}(H_j^c) \qquad j = 1.\cdots.N_c \tag{9}$$

$$H_j^{c\min}(P_j^c) \le H_j^c \le H_j^{c\max}(P_j^c) \qquad j = 1.\cdots.N_c \tag{10}$$

$$H_i^{h\min} \le H_i^h \le H_i^{h\max} \qquad i = 1.\cdots.N_h \tag{11}$$

$P_i^{p_{\min}}$ and $P_i^{p_{\max}}$ represent the minimum and the maximum output power limits of the *i*th thermal power unit, in MW, respectively. $P_j^{c_{\min}}(H_j^c)$, $P_j^{c_{\max}}(H_j^c)$, $H_j^{c_{\min}}(P_j^c)$ and $H_j^{c_{\max}}(P_j^c)$ are the linear inequalities that define the feasible operating region of the *j*th CHP unit. $H_i^{h_{\min}}$ and $H_i^{h_{\max}}$ are the minimum and the maximum outputs heat of the *k*th heat-only unit, respectively.

3. Methodological Framework

3.1. Imperialist Competitive Algorithm

ICA for the first time is presented in 2007, inspired by the social-human phenomenon [23]. Similar to the other evolutionary algorithms, this algorithm also starts with initial random populations. Any individual of an empire is called a country. There are two types of countries; colony and imperialist state that collectively form empires. Imperialistic competitions among these empires develop the basis of the ICA. During this competition, weak empires collapse and powerful ones take possession of their colonies. Imperialistic competitions converge to a state in which there is only one empire and its colonies are in the same position and have the same cost as the imperialist, which represents the best solution of the matching problem.

First, the number of initial countries and the number of variables are determined. Then N_{imp} of most powerful countries are selected to form the empires. The remaining N_{col} of the population will be the colonies which each of them belongs to an empire. The imperialist countries absorb the colonies towards themselves using the absorption (assimilation) policy. The absorption policy makes the main core of this algorithm and causes the countries move towards to their minimum. The total power of each empire is determined by the power of both parts: the imperialist power plus percent of its average colonies power. Pursuing assimilation policy, the imperialist states tried to absorb their colonies and make them a part of themselves. More precisely, the imperialist states made their colonies to move toward themselves along different social-political axis such as culture, language and religion. In the ICA, this process is modeled by moving all of the colonies toward the imperialist along different optimization axis. This movement is shown in Fig. 2 in which the colony moves toward the imperialist by x units and is reached from the previous position "$Pos_{colony\ of\ empire}^{Old}$" to the new position "$Pos_{colony\ of\ empire}^{New}$". If the distance between colony and imperialist is shown by d, x is a random variable with uniform (or any proper) distribution. New position of the colony is given as follows:

$$Pos_{colony\ of\ empire}^{New} = Pos_{colony\ of\ empire}^{Old} + x \tag{12}$$

$$x \sim U(0, \beta \times d) \tag{13}$$

where β is a number greater than 1 and in the most implementation a value of about 2 results in good convergence.

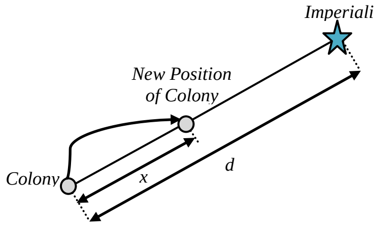

Fig (2): Moving Colonies toward their Relevant Imperialist (Assimilation Policy in the ICA Algorithm).

If a colony reaches a better point than an imperialist in its movement towards the imperialist country (equal to having more power than the country), it will replace with imperialist country. This causes the algorithm to continue with the imperialist country in a new location and in this time it is the new imperialist country which begins to apply assimilation policy for its colonies. The imperialistic competition consists in the dispute between empires in order to conquer the colonies of other empires. This event makes the most powerful empires increase their powers, while the weakest empires tend to decrease their power over time. The imperialistic competition can be modeled by choosing the weakest colony from the weakest empire to be disputed among the other empires. After a while, all the empires except the most powerful one will collapse and all the colonies will be controlled by this unique empire. More details on ICA can be found in [23].

3.2. Modified Imperialist Competitive Algorithm

As previously mentioned, assimilation policy in the imperialist competitive algorithm is affected only by the properties of their relevant imperialist whereas in the real world the impact of the most powerful empire on other colonies can also clearly be seen and the strongest imperialist tried to absorb the colonies and make them a part of itself. Indeed, the relevant imperialist and the most powerful imperialist attract the colony along different optimization axis as language and culture. In the proposed method, in addition to considering the effect of the central imperialist, the influence of the strongest empire in the various social-political aspects is also considered. To enrich the searching behavior and to avoid being trapped into local optimum, assimilation process in the ICA algorithm is changed and a new absorbing process is introduced. In the modified ICA, the assimilation policy is modeled by moving all the colonies toward the relevant imperialist and the most powerful empire. This movement is shown in Fig. 3, in which a colony moves toward the relevant imperialist by x_1 units and also moves toward the most powerful imperialist by x_2 units and finally reach from the previous position $Pos^{Old}_{colony\ of\ empire}$ to a new position $Pos^{New}_{colony\ of\ empire}$.

If the distance between the colony and relevant imperialist is shown by d_1 and the distance between colony and the strongest empire is shown by d_2, x_1, x_2 are random variables with uniform (or any proper) distribution and are defined as following:

$$x_1 \sim U(0.\beta_1 \times d_1) \quad (14)$$

$$x_2 \sim U(0.\beta_2 \times d_2) \quad (15)$$

Then new position of the colony can be defined by:

$$Pos^{New}_{colony\ of\ empire} = \lambda[Pos^{Old}_{colony\ of\ empire} + x_1 + x_2] \quad (16)$$

and λ is also given as follows:

$$\lambda = \frac{2}{\left|2 - (\beta_1 + \beta_2) - \sqrt{(\beta_1 + \beta_2)^2 - 4(\beta_1 + \beta_2)}\right|} \quad (17)$$

where constant β_1 pulls the colonies towards best local position whereas β_2 pulls it towards the best global position. A proper choice for these coefficients can be a value of about 2 for β_1 and about ۱۰ for β_2 in most of implementations. However, depending on the optimization problem, the coefficient may need to be changed. So, convergence and solution quality of the algorithms depends on the proper choice of coefficients. Relatively higher value of β_1, compared with the β_2, results in the roaming of individuals through a wide search space. On the other hand, a relatively high value of the social component leads particles to a local optimum prematurely. Therefore, setting the parameters is a key factor to find accurate and efficient solutions.

In population-based optimization methods, the policy is to encourage individuals to roam through the entire search space during the initial part of the search, without clustering around local optima. During the latter stages, convergence towards the global optima is encouraged to find the optimal solution efficiently [28-30].

So, the MICA technique with the time-varying coefficients (TVC) is proposed in this paper, to solve CHPED problems.

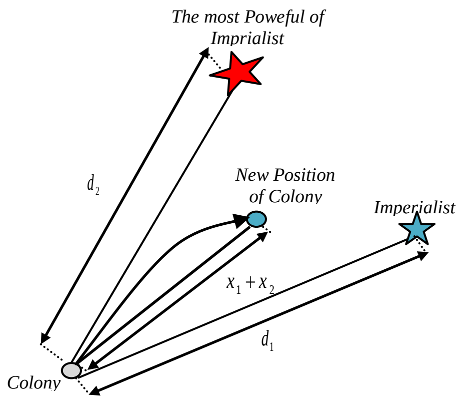

Fig (3): Assimilation Policy in the MICA Algorithm by Affecting of the most Powerful Empire and Relevant Imperialist.

The idea behind TVC is to enhance the global search in the early part of the optimization and to encourage the colonies to converge towards the global optima at the end of the search. This is achieved by changing the coefficients with time in such a manner that β_1 is reduced while the social component β_2 is increased as the search proceeds.

This modification can be mathematically represented as follows:

$$\beta_1 = (\beta_{1f} - \beta_{1i})\frac{iter}{iter_{\max}} + \beta_{1i} \quad (18)$$

$$\beta_2 = (\beta_{2f} - \beta_{2i})\frac{iter}{iter_{\max}} + \beta_{21i} \quad (19)$$

β_{1i}, β_{1f}, β_{2i} and β_{2f} are initial and final values of β_1 and β_2, respectively.

The flowchart of the proposed MICA is shown in Fig. 4.

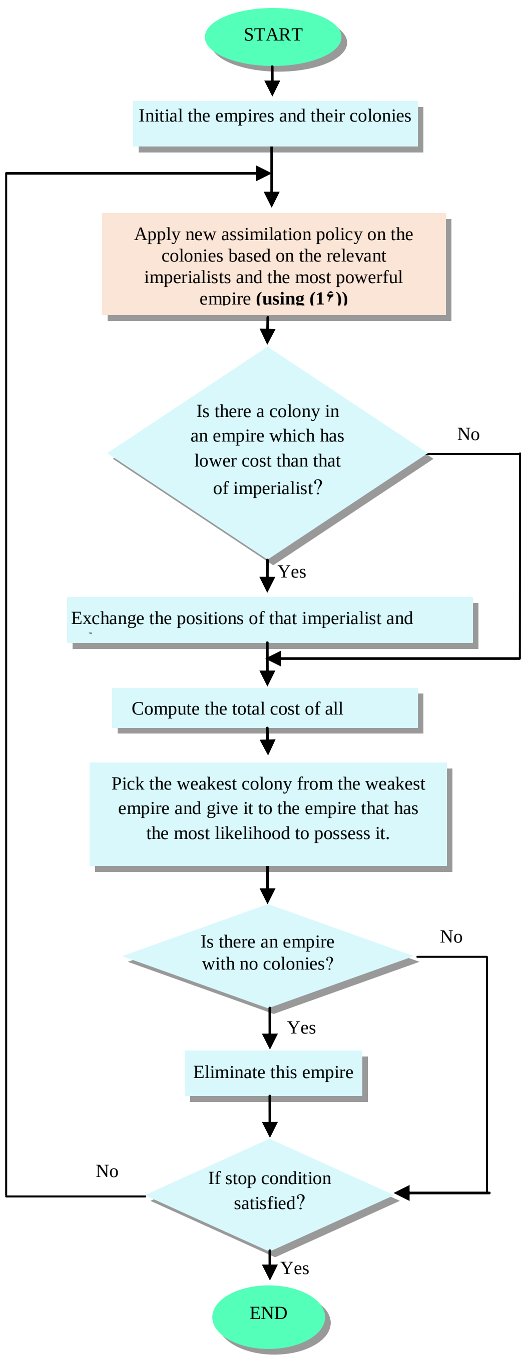

Fig (4): The Flowchart of the Proposed MICA Algorithm.

4. Application of MICA to the Problem

This section describes the procedural steps for the implementation of the proposed algorithm to the CHPED problem described above. In the CHPED problem, the real power output of the thermal conventional and cogeneration units and the heat output of cogeneration and heat-only units are considered as decision variables and are used to form the objective function of the problem. MICA approach implementation for solving CHPED can be summarized as the following steps:

Step 1*: Input to the necessary data:*

At this stage, the required data to solve the CHPED problem and necessary parameters for MICA are defined.

Step 2: *Generate the initial population:*

The problem independent variables are initialized somewhere in their feasible numerical range. The independent variables such as real power output of $N_p - 1$ number of generating units, $N_h - 1$ number of heat only units and real power and heat output of the CHP units are initialized randomly within their specified operating limits as follows:

$$P_{ij} = P_j^{\min} + rand \times (P_j^{\max} - P_j^{\min}) \quad j = 1.....N_p - 1.N_p + 1.....N_p + N_c \tag{20}$$

$$H_{ij} = P_j^{\min} + rand \times (P_j^{\max} - P_j^{\min}) \quad j = 1.....N_h - 1.N_h + 1.....N_h + N_c \tag{21}$$

where $rand\,(0,1)$ is a random generated number between 0 and 1, and has uniform distribution. In order to meet the equality constraints of the power demand and heat demand, power generation of the N_pth power generating unit without considering the loss and heat output of the N_hth heat generating unit are evaluated as follows:

$$P_{N_p} = P^{\text{demand}} + P^{\text{loss}} - \sum_{j=1}^{N_c} P_j - \sum_{i=1}^{N_p-1} P_i \tag{22}$$

$$P_{N_p} = H^{\text{demand}} + - \sum_{j=1}^{N_c} H_j - \sum_{k=1}^{N_h-1} H_k \tag{23}$$

Step 3: *Calculate the fitness of the initial population:*

In order to assess the situation of each country, the objective function using (1) is defined. The objective function should be minimized satisfying all constraints.

Step 4: *Determine the initial empires and colonies:*

Based on the cost function, initial empires and their colonies are identified.

Step 5: *Update the new position of colonies:*

MICA colonies in the new position will be updated as follows:

$$Pos_{colony\ of\ empire}^{New} = \lambda[Pos_{colony\ of\ empire}^{Old} + x_1 + x_2]$$

$$x_1 \sim U\left(0.\left((\beta_{1f} - \beta_{1i})\frac{iter}{iter_{\max}} + \beta_{1i}\right) \times d_1\right) \tag{24}$$

$$x_2 \sim U\left(0.\left((\beta_{2f} - \beta_{2i})\frac{iter}{iter_{\max}} + \beta_{2i}\right) \times d_2\right) \tag{25}$$

Step 6: *Evaluate the colonies:*

At this stage, the new position of the colonies is evaluated using the objective function and if the colonies have reached a higher status than their imperialists, their places are changed with each other. Then the algorithm continues with the new imperialists, and at this time the new imperialists start to do assimilation policy on their colonies.

Step 7: *Imperialistic competition:*

Any empire that is not able to succeed in this competition and can't increase its power (or at least prevent decreasing its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately will collapse.

Step 8: *Check stopping criteria:*

At this step exit condition of the loop is checked. If the convergence criteria are met, the loop breaks and the best imperialism results are shown as optimal solution, otherwise, it returns to Step 5. In the proposed method, if all empires collapse and only one empire remained or the maximum number of iterations is reached then, the stop condition is met.

5. Simulation Results and Discussion

To evaluate the performance and ability of the modified ICA, this algorithm is implemented and tested on several types of systems to validate the efficiency and scalability of the proposed method. In order to demonstrate the scalability of the proposed method, scale up is conducted based on a 24-unit system contain 13 thermal units, 6 cogeneration units and 5 heat-only units. The commercial software MATLAB has been used for implementing the proposed algorithm, which has been performed on an Intel Core i7-7500U, 2.70 GHz laptop with 12 GB of RAM memory.

5.1. Setting the Simulation Parameters

In all experiments, the number of the initial countries and maximum iteration of both ICA and MICA algorithm are 80 and 1000, respectively. They are assumed unless the information is clearly mentioned in the case study.

In the ICA algorithm, β and ξ coefficients have been considered 2 and 0.02, respectively. In the proposed algorithm, the initial and final values of β_1 and β_2 have also been chosen 0.5 and 2.5, respectively and ξ coefficient is selected equal to 0.02. It should be noted that due to the random nature of the ICA and MICA methods, 30 independent experiments have been carried out to compare the convergence characteristics and the quality of problem solving.

5.2. Case Study 1: Small Scale Systems (4 unit-System without Considering Transmission Losses, 5 Unit-System without Considering Transmission Losses with Three Different Scenarios)

A. 4-Unit Test System

The first test case is a simple system proposed by [9] and is presented to demonstrate the quality and performance of the proposed method. The studied system consists of a conventional power-only unit, two CHP units and a heat-only unit. All of constraints and cost functions of the conventional thermal units (unit 1) and a heat-only (unit 4) are assumed linear and are shown in the Eqs. (26) to (28), respectively. CHP units' data as the cost function parameters are presented in [9]. The system power demand and heat demand are 200 MW and 115 MWth, respectively. The fuel cost function for the units in the system have already been mentioned in (4).

$$\min \sum_{i=1}^{1} C_i(P_i^p) + \sum_{j=1}^{2} C_j(P_j^c, H_j^c) + \sum_{k=1}^{1} C_k(H_k^h) \quad (\$/\mathrm{h}) \tag{26}$$

$$C_1(P_1) = 50P_1 \qquad 0 \le P_1 \le 150 \text{ MW} \tag{27}$$

$$C_4(H_4) = 23.4H_4 \qquad 0 \le H_4 \le 2695.2 \text{ MWth} \tag{28}$$

Computational results obtained from this example by ICA and MICA are compared with other methods like LR [8], genetic algorithms [9-10] as IGA_MU, IGA and SARGA, TAVAC-PSO algorithm [29] and the comparing results are presented in Table 1. LR and SQP methods are converged to 9257.1 \$ and other algorithms have also reached 9257.07 \$. Table 1 shows the satisfactory solution results of this problem by MICA. Despite the closeness of the MICA to results of procedures such as IGA_MU (9257.07 \$), the best result for solving this problem is for MICA (9257.0652 \$) which is most likely to be a global optimal point for this problem. Also, according to the results, it can be seen that the proposed algorithm satisfies all constraints and all CHP units work in the defined feasible region.

Table (1): Comparison of Obtained Results by Different Methods for Case Study 1 Section A.

Methods	Output						
	P_1	P_2	P_3	H_2	H_3	H_4	Total Cost (\$)
LR [8]	0	160	40	40	75	0	9257.1
IGA_MU [10]	0	160	40	39.99	75	0	9257.07
SQP [7]	0	160	40	40	75	0	9257.1
SARGA[9]	0	159.99	40.01	39.99	75.00	0	9257.07
MADS [32]	0	160	40	40	75	0	9257.07
IGA [10]	0	160	40	39.99	75	0	9257.09
TAVACPSO [29]	0	160	40	40	75	0	9257.07
BD [22]	0	160	40	40	75	0	9257.07
ICA	0	160	40	40	75	0	9257.07
MICA	**0**	**159.9996**	**40.0004**	**39.9910**	**75.0089**	**0**	**9257.0221**

B. 5-Unit Test System with Three Different Scenarios

In order to further test the proposed MICA in facing small-size systems and comparing it with the other methods, another experiment with different scale, power and heat demands have been conducted. The system of Section B first is presented by Vasebi *et al.* in 2007 [16]. It consists of a conventional power unit, three cogeneration units and one heat-only unit. Experimental system for three different power and heat demand is considered. Power and heat demanded for three different scenarios are respectively: 300MW and 150 MWth (scenario I), 250 MW and 175 MWth (scenario II) and 160 MW and 220 MWth (scenario III). Cost functions and constraints of conventional and heat-only units are expressed in Eqs. (29)-(31), respectively. The cost function parameters of the CHP units are presented in [16].

$$C_1(P_1) = 254 \cdot 8863 + 7 \cdot 6997 P_1 + 0 \cdot 00172 P_1^{\,2} + 0 \cdot 000115 P_1^{\,3} \quad (29)$$

$$C_1(P_1) = 254.8863 + 7.6997P_1 + 0.00172P_1^2 + 0.000115P_1^3$$
$$0 \le P_1 \le 35 \text{ MW} \quad (30)$$

$$C_5(H_5) = 950 + 2.0109H_5 + 0.038H_5^2$$
$$0 \le H_5 \le 60 \text{ MWth} \quad (31)$$

Table (2): Comparison of Obtained Results by Different Methods for Case Study 1 Section B.

Scenarios	Demand		Methods	Output								
	P^{demand}	H^{demand}		P_1	P_2	P_3	P_4	H_2	H_3	H_4	H_5	Total Cost ($)
I	300	150	CPSO [19]	135.0000	40.7309	19.2728	105.0000	64.4003	26.4119	0.0000	59.1955	13692.5212
			TVAC-PSO [19]	135.0000	41.4019	18.5981	105.0000	73.3562	37.4295	0.0000	39.2143	13672.8892
			GSA [31]	135.0000	41.7806	18.1736	105.0000	74.0890	37.3336	0.0000	38.5713	13,671.1490
			EMA [32]	135.0000	40.7163	19.2837	105.0000	73.7022	36.7183	0.0000	39.5829	13,672.7407
			BD [27]	135.0000	40.7687	19.2313	105.0000	73.5957	36.7759	0.0000	39.6284	13672.83
			ICA	134.9963	40.7309	19.2728	105	64.4003	26.4119	0.0000	59.1878	13692.4191
			MICA	**135.0000**	**40.7472**	**19.1560**	**104.9969**	**73.6467**	**36.7714**	**0.0036**	**39.5781**	**13668.8326**
II	250	175	CPSO [19]	135.0000	40.3446	10.0506	64.6060	70.9318	39.9918	4.0773	60.0000	12132.8579
			TVAC-PSO [19]	135.0000	40.0118	10.0391	64.9491	74.8263	39.8443	16.1867	44.1428	12117.3895
			GSA [31]	135.0000	39.9998	10.0000	64.9807	74.9844	40.0000	17.8939	42.1095	12,117.3700
			EMA [32]	135.0000	40.0000	10.0002	64.9997	74.9980	40.0001	14.0624	45.9394	12,117.0785
			BD [27]	135.0000	40.0000	10.0000	65.0000	75.0000	40.0000	14.4029	45.5971	12116.60
			ICA	129.7710	40.4355	14.0021	65.7911	75.1881	27.3526	22.3190	50.1401	12253.1006
			MICA	**135.0000**	**39.9994**	**9.9997**	**64.9008**	**75.0003**	**40.0003**	**14.4391**	**45.5601**	**12113.5990**
III	160	220	CPSO [19]	35.5972	57.3554	10.0070	57.0587	89.9767	40.0025	30.0232	60.0000	11781.3690
			TVAC-PSO [19]	42.1433	64.6271	10.0001	43.2295	96.2593	40.0001	23.7407	60.0000	11758.0625
			GSA [31]	39.2183	60.1454[a]	10.0000	50.6296	92.8700[a]	40.0000	27.1044	60.0000	11745.5546
			EMA [32]	42.1433	64.6378	10.0000	43.2188	96.2653	40.0000	23.7338	60.0000	11757.9124
			BD [27]	42.1454	64.6296	10.0000	43.2250	96.2614	40.0000	23.7386	60.0000	11758.06
			ICA	35.5789	57.3554	10.0070	57.0587	89.9767	40.0025	30.0232	59.9976	11781.2024
			MICA	**41.6965**	**63.8884**	**10.1123**	**43.3026**	**95.6224**	**40.0485**	**24.2298**	**60**	**11754.9219**

This problem has already been solved using different evolutionary methods. The minimum cost obtained by other methods for solving this problem for comparing with performance of MICA is given in Table 2 that shows the best solution obtained from the proposed method and reported solutions by other authors. It is observable from Table 2 that after the implementation of the MICA on the scenario I, the total cost is equal to 13668.8326 $. This cost is much less than best results of CPSO [19] (13692.5212 $), TVAC-PSO [19] (13672.8892 $), GSA [31] (13,671.1490), EMA [32] (13,672.7407), BD [27] (13672.83) and ICA (13692.4191 $) methods. Scenario II in the previous scenario has less power and much heat demand than previous scenarios. The best total cost obtained by applying the MICA on Scenario II, is equal to 12113.5990 $, which is significantly lower than the results of the CPSO [19] with the best cost 12,132.8579 $ and ICA with the cost of 12253.1006 $. Also, despite being close to the results of TVAC-PSO [19], GSA [31], EMA [32] and BD [27], the obtained cost is less than the cost of them. Table 2 presents the optimal heat and power dispatches of scenario III. According to the results, in spite of multiple local optimal points, the proposed method is able to find a minimum cost of 11754.9219 $ which is 0.2۳%, 0.027%, 0.08%, 0.025% and ۰,۰۲۷% better than CPSO [19], TVAC-PSO [19], EMA [32], BD [27] algorithms respectively and also 0.22% is better than the result of ICA. It is clear from the results that the proposed MICA method can avoid the shortcoming of premature convergence and can approach to the global optimum.

5.3. Case Study 2: Medium Scale Systems (24 Unit-System Considering Valve Point Effects and48 Unit-System Considering Valve Point Effects)

A. 24-Unit Test System Considering Valve Point Effects

In this case study, the simulation consists of medium-scale experiments to demonstrate the validity and efficiency of the proposed algorithm. Conventional thermal units based on the 13-unit standard ELD test system which has a lot of local minimal and is one of the challenging ELD test cases [19, 33], which has been proposed by Mohammadi *et. al* [19].

Table (3): Optimal Dispatch Results of ICA and MICA Methods for Case Study 2 Section A.

Output	Methods		Output	Methods	
	ICA	MICA		ICA	MICA
P_1	628.3188	۶۲۸,۳۱۸۵	P_{16}	117.4848	۸۰,۹۹۲۴
P_2	63.1622	۲۹۹,۱۹۵۵	P_{17}	45.9155	۴۰,۰۰۱۰
P_3	0.0014	۲۹۹,۱۶۱۴	P_{18}	9.9991	۱۰,۰۰۱۳
P_4	179.9162	۱۰۹,۸۶۶۵	P_{19}	42.1170	۳۴,۹۷۸۴
P_5	179.9147	۱۰۹,۸۶۶۵	H_{14}	125.2766	۱۰۴,۸۱۲۴
P_6	179.9162	۱۰۹,۸۶۶۲	H_{15}	80.1160	۷۵,۰۰۸۲
P_7	179.9162	۵۹,۹۹۹۹	H_{16}	125.2754	۱۰۴,۸۰۱۳
P_8	179.9162	۱۰۹,۸۶۵۸	H_{17}	80.1074	۷۵,۰۰۹۴
P_9	179.9162	۱۰۹,۸۵۷۲	H_{18}	39.9993	۴۰,۰۰۴۸
P_{10}	39.9999	۳۹,۹۹۲۸	H_{19}	23.2354	۱۹,۹۹۴۷
P_{11}	50.0917	۷۷,۰۳۲۲	H_{20}	415.9857	۴۷۰,۳۲۸۷
P_{12}	55.0004	۵۴,۹۹۸۶	H_{21}	60.0009	۶۰,۰۰۹۹
P_{13}	55.0005	۵۴,۹۹۳۲	H_{22}	60.0009	۶۰,۰۰۹۹
P_{14}	117.4866	۸۱,۰۱۲۲	H_{23}	120.0009	۱۲۰,۰۰۹۹
P_{15}	45.9255	۳۹,۹۹۹۵	H_{24}	120.0009	۱۲۰,۰۰۹۹
Total Cost ($)					
ICA			59431.8103		
MICA			**57823.1426**		

The system consists of 13 power-only units, 6 cogeneration units and 5 heat-only units. Power and heat demands are 2350MW and 1250MWth, respectively. All data units is presented in [19]. Detailed solutions to solve this CHPED problem by ICA and MICA are presented in Table 3. Table 4 shows also Comparison of the best, average and worst results obtained from this method and the results of other algorithms. It can be observed that the total cost obtained by this method (57823.1426 $) is significantly less than the cost of the procedures TLBO [5] (58006.9992 $), OTLBO [5] (57856.2676 $), CPSO [29] ((59736.2635 $, TVAC-PSO [29] (58122.7460 $) and ICA (59431.8103 $) which indicates the ability of the algorithm in dealing with the various-scale problems. Obtained results by the proposed method were respectively 0.27%, 0.012%, 3.26%, 0.47% and 2.74% which are less than the obtained costs of the TLBO [5], OTLBO [5], CPSO [29], TVAC-PSO [29] and ICA methods. Also, the worst result obtained by the proposed MICA method is 57954.9118 $, which is less than the best result of ICA that is59431.8103 $. This demonstrates the high efficiency of the proposed absorption strategy, which is used in the classical ICA algorithm and improves dramatically the local and global search ability. Also, it is noteworthy that the worst result obtained from the proposed method is better than the best results of the TLBO [5], CPSO [32] and TVAC-PSO [29].

Table (4): Comparison of Obtained Results by Different Methods for Case Study 2 Section A.

Methods	Best Cost ($)	Average Cost ($)	Worst Cost ($)
TLBO [7]	58006.9992	58014.3685	58038.5273
OTLBO [7]	57856.2676	57883.2105	57913.7731
GSA [31]	58,121.8640	58,122.7460	59,736.2635
EMA [32]	57,825.4792	57,832.7361	57,841.1469
CPSO [19]	59736.2635	59853.4780	60076.6903
TVAC-PSO [19]	58122.7460	58198.3106	58359.5520
ICA	59431.8103	59780.9874	60188.2073
MICA	**57823.1426**	**57845.9767**	**589421.0543**

B. 48-Unit Test System Considering Valve Point Effects

To better illustrate the validity of MICA, another system that its number of units is twice as much as the number of units in the previous section used in this section. The system contains 26 thermal units, 12 CHP units and 10 heat-only units. The total power demand of this case is 4700 MW and heat demand is 2500 MWth. The unit characteristics of this system are similar to case study 2 section A and obtain by duplicating data of the previous section. Table 5 shows accurate heat and power dispatches using of ICA and MICA algorithms. Also, the best, worst and average optimal solutions by MICA and other algorithms can be seen in Table 6 and are compared with the obtained results of the TLBO [7], OTLBO [7], CPSO [19], CSA [34] TVAC-PSO [19] techniques and classical ICA. According to the presented results, the final cost of MICA is 116530.8610 $ which is significantly lower than other approaches, so, it is clear that the proposed method does not suffer from premature convergence and is able to find optimal solutions than other methods. However, the obtained power and heat results from all of methods confirm that the equality and inequality constraints are fulfilled by MICA and the proposed approach is operated in a bounded heat versus power plane.

Table (5): Optimal Dispatch Results of ICA and MICA Methods for Case Study 2 Section B.

Output	Methods		Output	Methods	
	ICA	MICA		ICA	MICA
P_1	538.5665	628.3185	P_{31}	10.9034	10.0881
P_2	76.4028	225.3250	P_{32}	37.9270	39.3100
P_3	68.6531	224.7586	P_{33}	109.3835	82.0192
P_4	135.5216	159.7814	P_{34}	61.1959	40.1102
P_5	161.9568	109.9063	P_{35}	111.9550	81.2957
P_6	145.3224	159.7354	P_{36}	55.3394	45.6646
P_7	120.3936	109.8683	P_{37}	22.9130	13.8709
P_8	147.8076	109.8734	P_{38}	54.7853	30.3870

P_9	135.9726	159.7348	H_{27}	108.0122	107.5957
P_{10}	112.0880	40.9267	H_{28}	87.6785	125.4914
P_{11}	108.2171	41.1113	H_{29}	104.7373	105.2105
P_{12}	74.2195	55.1796	H_{30}	88.4668	82.6853
P_{13}	65.2589	92.4469	H_{31}	40.3868	40.0381
P_{14}	248.0558	448.7989	H_{32}	21.3115	21.9595
P_{15}	299.2280	225.5280	H_{33}	120.5256	105.3725
P_{16}	299.6861	75.5055	H_{34}	92.0441	75.0960
P_{17}	142.5869	160.1166	H_{35}	122.1583	104.9665
P_{18}	138.8223	110.1600	H_{36}	88.2426	79.8908
P_{19}	141.4212	159.7385	H_{37}	45.4608	41.6593
P_{20}	142.9812	159.7790	H_{38}	28.9895	17.9036
P_{21}	119.5467	159.7420	H_{39}	417.0202	436.0609
P_{22}	139.5290	160.1720	H_{40}	59.5362	60.0009
P_{23}	77.8037	40.2144	H_{41}	59.9175	60.0009
P_{24}	81.7250	40.3064	H_{42}	119.9926	120.0009
P_{25}	110.3924	92.6548	H_{43}	118.4968	120.0009
P_{26}	111.6903	92.4681	H_{44}	418.2604	436.0611
P_{27}	95.1582	85.9808	H_{45}	59.7099	60.0009
P_{28}	54.6874	98.4890	H_{46}	59.9816	60.0009
P_{29}	86.2998	81.7305	H_{47}	119.2701	120.0010
P_{30}	55.6011	48.9018	H_{48}	119.7994	120.0010
Total Cost ($)					
ICA			119499.3441		
MICA			**116530.8610**		

Table (6): Comparison of Obtained Results by Different Methods for Case Study 2 Section B.

Solution technique	Best Cost ($)	Average Cost ($)	Worst Cost ($)
TLBO [7]	116739.3640	116756.0057	116825.8223
OTLBO [7]	116579.2390	116613.6505	116649.4473
CPSO [19]	119708.8818	NA*	NA*
CSA [34]	116843.300	117245.6	117636.1
TVAC-PSO [19]	117824.8956	NA*	NA*
ICA	119499.3441	119709.2169	119954.2551
MICA	**116530.8610**	**116582.1498**	**116594.7520**

* Not available in the referred literature.

5.4. Case Study 3: Large Scale Systems (72 Unit-System Considering Valve Point Effects and 96 Unit-System Considering Valve Point Effects)

In order to better assess the ability of the proposed algorithm and test its performance in dealing with large-sized problems, two large-scale systems considering valve point effects is implemented which are presented for the first time in in Ref. [11]. and include 72 and 96 units.

A. 72-Unit Test System Considering Valve Point Effects

The new proposed system consists of 39 conventional thermal units, 18 cogeneration units and 15 heat-only units. The system data is based on a 24-unit system and is achieved by the triple repetition of that system. Power and heat system demands are 7050MW and 3750MWth, respectively. Power and heat dispatching results by ICA and MICA algorithms are described in Table 7. The total cost obtained by the proposed MICA and ICA are 173642.8608 $ and 181846.7024 $, respectively, which the best cost of MICA is 8203.8416 $ and is less than the achieved cost by ICA algorithm. The results show that the MICA is an accurate and efficient algorithm for dealing effectively with the difficult CHP problems and without using the proposed assimilation strategy, the classical ICA can easily trap in local optimal and shows poorer results compared with MICA which uses a new assimilation strategy. It is noteworthy that the CHPED problem is more complex by increasing the size, particularly in the non-smooth and non-convex problems. Therefore, the overall performance of each algorithm decreases by increasing of the problems size. However, the proposed algorithm has acceptable performance and achieves good optimal solutions in solving the 72 units with 90 variables problem. The presented results in Table 8 confirmed these issues. The initial population and maximum iterations for this problem are assumed 100 and 2000, respectively.

B. 96-Unit Test System Considering Valve Point Effects

The new 96-unit system is a large system to demonstrate the effectiveness of the proposed algorithm in solving the practical problems with large dimensions. The system consists of 52 conventional power generation units, 24 CHP units and 20 heat-only units that simply is achieved by expanding the 24-unit system data. The degree of complexity of the CHP dispatch problem is related to the system-size. The mutual dependencies of heat-power capacity make it hard to find a feasible region, not to mention the optimal capacity. The larger system-size increases the non-linearity as well as the number of equality and inequality constraints in the CHP dispatch problem [35]. The Number of decision variables of this problem is 120 that indicates the complexity of the problem. The best results obtained by the ICA and MICA are presented in Table 8. The results show that the proposed algorithm is able to satisfy all constraints of the problem and is able to find a more optimal solution than ICA. So, it can be said the proposed algorithm has high resolution quality, especially in solving the large-sized problems. In order to demonstrate the convergence of ICA and MICA methods for solving CHPED problems, convergence characteristics of these methods, for example, for case study 3 section B, is shown in Fig. 5. To solve this problem, the initial population of 100 and a maximum of 2000 iterations are assumed.

Table (7): Optimal Dispatch Results of ICA and MICA Methods for Case Study 3 Section A.

Output	Methods		Output	Methods	
	ICA	**MICA**		ICA	**MICA**
P_1	190.7873	564.9184	P_{46}	87.2573	80.9909
P_2	206.3452	299.1993	P_{47}	83.4423	39.9908
P_3	156.7992	224.3995	P_{48}	112.6863	80.9995
P_4	115.6038	109.8666	P_{49}	40.5056	39.9980
P_5	115.1675	109.8665	P_{50}	12.4469	9.9926
P_6	145.2583	109.8666	P_{51}	17.7242	34.9911
P_7	160.2530	109.8664	P_{52}	97.7451	80.9911
P_8	144.9226	109.8666	P_{53}	103.6941	39.9909
P_9	113.8495	109.8666	P_{54}	103.1622	80.9995
P_{10}	83.2285	39.9905	P_{55}	60.1970	39.9980
P_{11}	114.8828	39.9907	P_{56}	15.3798	9.9926
P_{12}	57.5228	55.0001	P_{57}	62.7017	34.9905
P_{13}	90.3005	55.0000	H_{40}	111.8438	104.8062
P_{14}	448.7558	628.3185	H_{41}	93.0473	75.0072
P_{15}	299.2448	299.1993	H_{42}	139.2308	104.8038
P_{16}	299.2128	299.1993	H_{43}	110.9482	75.0082
P_{17}	63.6316	109.8666	H_{44}	47.0245	40.0004
P_{18}	98.5883	109.8666	H_{45}	4.1395	20.0036
P_{19}	172.9762	159.7331	H_{46}	108.3105	104.8005

P_{20}	178.9187	109.8639	H_{47}	112.5018	75.0007
P_{21}	177.1266	109.8660	H_{48}	122.5504	104.8053
P_{22}	160.7478	109.8666	H_{49}	75.4359	75.0069
P_{23}	40.2516	39.9951	H_{50}	41.0415	40.0011
P_{24}	62.9404	40.0001	H_{51}	2.4728	20.0002
P_{25}	118.3770	54.9953	H_{52}	114.1956	104.8006
P_{26}	92.4453	54.9918	H_{53}	129.9838	75.0007
P_{27}	448.8109	628.3188	H_{54}	117.2352	104.8053
P_{28}	218.5126	299.1992	H_{55}	92.4001	75.0069
P_{29}	59.4582	299.0638	H_{56}	18.4776	40.0011
P_{30}	162.2253	109.8661	H_{57}	32.5910	20.0002
P_{31}	109.4150	109.8665	H_{58}	428.4352	470.4922
P_{32}	171.3456	159.7331	H_{59}	59.9965	60.0100
P_{33}	175.8149	109.8666	H_{60}	59.9343	60.0100
P_{34}	156.6411	109.8659	H_{61}	119.9932	120.0100
P_{35}	160.9804	109.8665	H_{62}	119.9852	120.0100
P_{36}	42.8263	39.9953	H_{63}	433.1106	470.2647
P_{37}	46.0230	39.9962	H_{64}	1.8680	60.0099
P_{38}	90.1878	55.0001	H_{65}	59.9679	60.0100
P_{39}	97.6710	54.9916	H_{66}	119.9944	120.0100
P_{40}	93.5506	81.0011	H_{67}	119.9991	120.0100
P_{41}	60.9055	39.9983	H_{68}	396.4278	470.2644
P_{42}	142.3551	80.9968	H_{69}	60.0005	60.0100
P_{43}	81.6472	39.9995	H_{70}	59.9714	60.0100
P_{44}	26.3897	9.9910	H_{71}	120.0002	120.0099
P_{45}	0.1563	34.9980	H_{72}	119.3565	120.0100
Total Cost ($)					
ICA			181846.7024		
MICA			**173642.8608**		

Table (8): Optimal Dispatch Results of ICA and MICA Methods for Case Study 3 Section B.

Output	Methods		Output	Methods	
	ICA	**MICA**		ICA	**MICA**
P_{1}	628.3190	502.0642	P_{61}	82.1448	80.9996
P_{2}	224.5221	299.1993	P_{62}	47.0820	39.9980
P_{3}	224.4710	224.3995	P_{63}	13.9366	9.9926
P_{4}	161.4762	109.8666	P_{64}	29.9989	34.9911
P_{5}	111.3439	109.8665	P_{65}	102.2237	80.9911
P_{6}	160.8654	109.8666	P_{66}	109.4620	39.9908
P_{7}	108.5931	109.8665	P_{67}	100.4924	80.9995
P_{8}	114.3767	109.8665	P_{68}	53.8352	39.9980
P_{9}	162.2904	109.8666	P_{69}	22.4173	9.9926
P_{10}	40.1482	39.9904	P_{70}	20.7867	34.9905
P_{11}	41.7847	39.9912	P_{71}	104.0357	80.9910
P_{12}	55.7697	55.0000	P_{72}	75.0282	39.9908

P_{13}	116.8735	55.0000	P_{73}	95.4412	80.9995
P_{14}	451.1011	628.3183	P_{74}	50.8429	39.9980
P_{15}	224.4753	299.1992	P_{75}	15.9830	9.9926
P_{16}	74.2867	299.1993	P_{76}	26.4996	34.9905
P_{17}	161.5653	109.8665	H_{53}	107.5327	104.8062
P_{18}	108.8009	109.8663	H_{54}	125.9673	75.0072
P_{19}	160.7853	159.7323	H_{55}	106.3386	104.8037
P_{20}	159.7224	109.8638	H_{56}	88.6605	75.0082
P_{21}	161.8797	109.8659	H_{57}	40.0309	40.0004
P_{22}	131.5898	109.8666	H_{58}	21.9708	20.0036
P_{23}	44.9350	39.9945	H_{59}	105.1469	104.8005
P_{24}	47.4198	40.0000	H_{60}	75.5610	75.0006
P_{25}	90.9249	54.9968	H_{61}	105.4429	104.8054
P_{26}	95.4558	54.9919	H_{62}	81.1144	75.0069
P_{27}	450.1927	628.3185	H_{63}	41.6875	40.0011
P_{28}	226.7237	299.1993	H_{64}	17.7267	20.0005
P_{29}	75.1030	299.1988	H_{65}	116.7111	104.8006
P_{30}	157.4396	109.8661	H_{66}	129.2096	75.0007
P_{31}	109.8845	109.8666	H_{67}	111.6395	104.8053
P_{32}	162.1369	159.7331	H_{68}	86.9440	75.0069
P_{33}	176.7750	109.8637	H_{69}	45.3055	40.0011
P_{34}	163.4927	109.8666	H_{70}	13.5398	20.0002
P_{35}	163.1571	109.8673	H_{71}	117.7280	104.8006
P_{36}	41.0573	39.9953	H_{72}	105.2385	75.0007
P_{37}	40.2377	39.9940	H_{73}	112.9048	104.8053
P_{38}	93.0677	54.9979	H_{74}	84.3601	75.0069
P_{39}	95.0943	54.9914	H_{75}	42.5645	40.0011
P_{40}	448.9955	628.3186	H_{76}	12.3498	20.0002
P_{41}	227.0345	299.1993	H_{77}	358.1764	470.5737
P_{42}	74.9066	299.1980	H_{78}	59.9999	60.0100
P_{43}	159.2037	109.8660	H_{79}	59.9960	60.0100
P_{44}	118.0485	109.8666	H_{80}	119.9809	120.0100
P_{45}	161.7393	159.7331	H_{81}	120.0009	120.0100
P_{46}	159.6920	109.8665	H_{82}	437.2219	470.2648
P_{47}	160.2331	109.8664	H_{83}	60.0000	60.0100
P_{48}	160.4884	109.8665	H_{84}	60.0009	60.0100
P_{49}	40.9685	39.9953	H_{85}	120.0000	120.0100
P_{50}	40.0636	39.9939	H_{86}	119.9978	120.0100
P_{51}	92.0630	54.9953	H_{87}	434.3301	470.2644
P_{52}	90.7863	54.9975	H_{88}	60.0009	60.0100
P_{53}	85.8709	81.0011	H_{89}	59.9989	60.0100
P_{54}	99.0405	39.9983	H_{90}	118.8831	120.0099
P_{55}	85.0034	80.9967	H_{91}	119.9603	120.0093
P_{56}	55.8236	39.9995	H_{92}	436.1627	470.2644
P_{57}	10.0713	9.9910	H_{93}	60.0009	60.0100

P_{58}	39.3492	34.9980	H_{94}	59.6094	60.0100
P_{59}	81.6172	80.9908	H_{95}	120.0005	120.0100
P_{60}	40.6489	39.9908	H_{96}	120.0009	120.0095
Total Cost ($)					
ICA			235860.8140		
MICA			**231494.8552**		

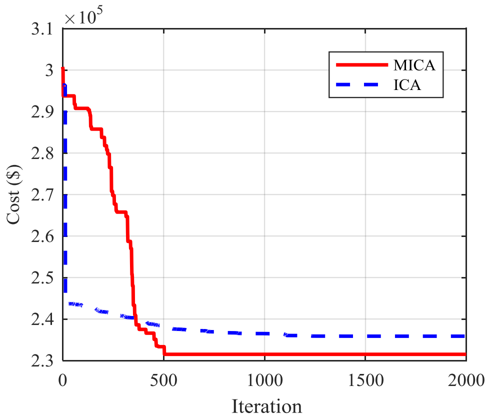

Fig (5): Convergence Cost Curve of ICA and MICA Methods for the Case Study 3 Section B.

6. Conclusion

Combining cogeneration units to the conventional ED problem increases the complexity of the problem. In order to solve the problem and satisfy all constraints of the CHPED problem, considering valve point effects and losses, a new algorithm based on the colonial competitive algorithm is proposed in this study. The proposed strategy uses a new assimilation policy which considers the impact of the most powerful empire besides the effect of other imperialists. Experimental systems with various units (4, 5, 24, 48, 72 and 96-unit) and constraints, with/without losses and valve point effects are applied to validate the modified algorithm. Quality of solutions, convergence characteristics and ability to find the near-global (maybe global) optimal solutions of the proposed method are obviously better than the classical ICA and the other state-of-the-art algorithms. Besides, the results demonstrate the high potential of MICA in solving non-convex with different-scale CHPED problems. Satisfactory performance of the MICA in this paper acknowledges that this method can be used as a suitable tool for solving many practical problems of power system in the future.

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