NON-CONVEX OPTIMISATION OF COMBINED ENVIRONMENTAL ECONOMIC DISPATCH THROUGH CULTURAL ALGORITHM WITH THE CONSIDERATION OF THE PHYSICAL CONSTRAINTS OF GENERATING UNITS AND PRICE PENALTY FACTORS

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Abstract: Four versions of cultural algorithm have been proposed to find an optimal solution of the combined environmental economic dispatch problem. The main objective of combined environmental economic dispatch is to simultaneously minimise two competitive objectives of fuel cost and emission, while satisfying various power system constraints such as the valve-point effect, emission costs, the prohibited operation zone, the ramp-rate limit, and the transmission losses. In order to solve this non-convex and non-continuous multi-objective optimisation problem with the cultural algorithm, the objective function has been converted to a single objective function using a technique called price penalty factor. Four different types of penalty factors have been examined in this paper. Three different test case systems with 5, 20, and 50 generating units have been implemented to investigate the performance and effectiveness of proposed algorithms. The cultural algorithm shows a superior performance in handling the combined environmental economic dispatch problem in comparison to other methods.

Key words: Combined environmental economic dispatch, cultural algorithm, price penalty factors, prohibited operating zones, ramp-rate limits, valve-point effect

NOMENCLATURE

Index

CA	Cultural algorithm
CEED	Combined environmental economic dispatch
CF	Cost function
PF	Penalisation factor
PPFs	Price penalty factors
POZ	Prohibited operating zone

Variables

a_i, b_i, c_i	Fuel cost coefficients of unit i
$\alpha_i, \beta_i, \gamma_i, \eta_i, \delta_i$	Emission cost coefficients of unit i
d_i, e_i	Fuel cost coefficients of unit i regarding valve-point effects
B_{ij}	$ijth$ element of the loss coefficient square matrix
B_{0i}	ith element of the loss coefficient vector
B_{00}	Loss coefficient constant
$B(t)$	Belief space at cultural algorithm
$F_{ct}(P)$	Total CEED generation cost
$f_{emc}(P)$	Emission cost function
$f_{gc}(P)$	Generation cost function
h_i	Coefficient of price penalty factor
$h_i^{max-max}$	Max-Max price penalty factor
$h_i^{max-min}$	Max-Min price penalty factor
$h_i^{min-max}$	Min-Max price penalty factor
$h_i^{min-min}$	Min-Min price penalty factor
$I_j(t)$	Closed interval at $N(t)$
l, u	The lower and upper bound which are initialised by the domain values
$L_j(t)$	Score of the lower bound at $N(t)$
N_G	Number of generating units
$N(t)$	Normative knowledge component of the cultural algorithm
N_{ij}	A normalised number for individual i and component j
n_s	Number of variables of situational component
n_x	Number of variables of normative component
nz_i	Number of prohibited zones for unit i
Ω	Sets of units having POZ
P_i	Power output of unit i
P_D	Load demand
P_L	Power transmission loss
P_i^0	Previous output power
P_{i,nz_i}^u	Upper bound of unit i at prohibited zone i

P_i^{min}, P_i^{max}	Minimum and maximum generation limits of the ith generating unit
$P_{i,l}^l, P_{i,l}^U$	Lower and upper bound of the lth prohibited zones of unit i
$P_{i,k}^l, P_{i,k}^U$	Lower and upper bound of the kth prohibited zones of unit i
$P_{i,nz_i}^l, P_{i,nz_i}^U$	Lower and upper bound of the nzth prohibited zones of unit i
$S(t)$	Situational knowledge component of the cultural algorithm
S_i	Spinning reserve from unit i
S_R	Total system spinning reserve requirement
S_i^{max}	Maximum spinning reserve contribution of unit i
δ_j	Step size of belief interval
$\delta_j^2(t)$	The variance of normalised number N_{ij}
$U_j(t)$	Score of the upper bound at $N(t)$
UR_i, DR_i	Up and down ramp rate limits of unit i
$X_j(t)$	Dimension of belief space at component j
$X_l(t)$	An accepted response
$x_{ij}(t)$	The mean of normalised number N_{ij}
$x_{lj}(t)$	An accepted response of the component j
$\acute{x}_{ij}(t)$	Influence function
$x_j^{min}(t), x_j^{max}(t)$	Minimum and maximum boundary of the closed interval at generation t
$\hat{y}(t)$	Best individual of the solution vector

1. INTRODUCTION

Economic dispatch (ED) is an optimisation task in the power system that attempts to determine the optimal distribution of power demand among the committed generating units for the purpose of minimising total operating cost while satisfying a set of equality and inequality system constraints. With increased environmental concerns and given that thermal power plants release a significant amount of pollutants such as sulphur oxides (SO_x), nitrogen oxides (NO_x), carbon monoxide (CO), and carbon dioxide (CO_2) into the atmosphere, it has become essential to not only minimise the fuel cost but also the emission level of these harmful gases. In [1], several scenarios of emission reduction such as the installation of pollution control devices, burning low-emission fuels, replacement of aged fuel burners and the use of renewable energy resources have been considered for a combined environmental economic dispatch (CEED) problem. The latter solution has become an attractive short term strategy due to its economic advantages and ease of implementation [2, 3]. CEED is a multi-objective optimisation problem that attempts to simultaneously minimise two competitive objectives of fuel cost and emission of gaseous pollutants which are both related to system constraints.

Various techniques have been proposed for the CEED problem. The majority of the algorithms can be categorised as either mathematical or evolutionary optimisation techniques. Mathematical techniques have fast computational time and are able to find near exact solutions for convex problems through a convex objective function and their respective domains, while sometimes they would fall into local minima or maxima. Some researchers have tried to develop mathematical methods to handle the CEED problem. Nanda et al. aimed to solve the CEED problem concerning the line power flow constraint by developing a classical technique based on coordination equations [4]. A single objective function using a linear combination of different objectives as a weighted sum was developed in [5]. Unfortunately, multiple runs are required for this method and it also fails to solve non-convex functions [6]. A nonlinear unconstrained/constrained multi-objective mathematical formulation based on a fast ε-constraint approach was introduced in [7] where fuel cost and environmental impact were treated as competing objectives.

The CEED problem becomes a nonlinear, non-convex and non-continuous optimisation problem when the real-world power system constraints such as valve point effect, prohibited zone, ramp rate limits, and transmission losses are considered [8–10]. It is impractical to find a unique optimal solution using mathematical techniques with respect to all these constraints. To tackle this issue, researchers have applied heuristic optimisation algorithms to solve the CEED problem. These methods usually deal with non-smooth non-convex functions but, as a drawback, the computational time is long since they carry out a population of potential solutions simultaneously. Applications of different heuristic techniques pertaining to the CEED problem have been reported in literature. In [8], the price penalty approach has been presented, where the bi-objective CEED problem was converted to a single objective through to the max-max price penalty factor, after which various heuristic techniques such as genetic algorithm (GA), evolutionary programming (EP), particle swarm optimisation (PSO), and differential evolution (DE) were applied to obtain and compare the solutions for the IEEE 30-bus system and 15-unit system. The valve-point effect and transmission losses were not considered in [8]. In [11], the applicability of biogeography-based optimisation technique to find the solution of CEED problem has been presented. The proposed algorithm was implemented in three, six and fourteen generator test systems and results were compared to the solutions based on Newton-Raphson, Tabu search, GA, non-dominated sorting genetic algorithm (NSGA), fuzzy logic controlled genetic algorithm, PSO and DE. A game theory based model was developed in [3] to address the multi-objective dynamic economic emission dispatch problem taking into account transmission losses. Senthil proposed a lambda based approach using EP to solve the CEED problem considering powering limits [12]. The algorithm was tested on a power system consisting of three and six generators. A gravitational search algorithm has been suggested for the solution of the CEED problem in [13–16] and various test cases with and without the valve-point effect and transmission losses were considered in these studies. Many other heuristic algorithms such as NSGA-II

[17, 18], bacterial foraging [19–21], enhanced firefly algorithm [22], advanced parallelised PSO [23], fuzzified multi-objective PSO [24], multi-objective chaotic PSO [25], opposition-based harmony search algorithm [26], bee colony [2] and several others have been reported in the literature to obtain a solution to the CEED problem.

Cultural algorithm (CA) is an evolutionary optimisation method which was first introduced by Reynolds in 1994 [27]. Cultural algorithm consists of an evolutionary population space (genetic component) and a belief space (cultural principals). CA was initially designed to handle single objective optimisation problems. To cope with multi-objective problems, either a hybrid optimisation algorithm should be developed or the multi-objective function should be converted to a single function. Few studies have successfully implemented CA for the solution to the CEED problem. In [28], evolutionary programming was embedded into CA for this purpose and constraints such as ramp rate limits, prohibited zone of operation, valve point loading effects and transmission losses were considered. The method was tested on three, six and fourteen generator systems. Rui Zhang et al. [6] developed a hybrid PSO-CA technique to address the CEED problem when considering prohibited operating zones and generator limits. Two test systems were implemented to verify efficiencies of the proposed method. A hybrid multi-objective cultural algorithm method was presented in [29] to carry out the optimal short-term environmental/economic hydrothermal scheduling. The proposed hybrid method combined a differential evolution (DE) algorithm into the framework of CA.

In this study, an approach based on the price penalty factor, i.e. ratio of fuel cost to emission value, has been used to convert the multi-objective combined emission and economic dispatch problem into a single objective function. To replicate a real-world power system, the following constraints of generating units such as ramp-rate limits, prohibited operating zones, valve-point effect, and transmission losses have been considered. The effectiveness of CA in handling complex CEED problems has been verified on three test systems with 5, 20 and 50 generating units and non-smooth fuel cost functions. Simulation results have been compared with other heuristic optimisation techniques such as biography based optimiser (BBO), restricted ant colony optimiser (ACOR), artificial bee colony (ABC), PSO, GA, hybrid GA and PSO (GAPSO), and firefly algorithm (FA). The main contributions of this paper are as follows: i) four different versions of cultural algorithm have been employed to solve CEED problem. To the best of authors' knowledge, a similar study has never been reported; ii) the impact of four different types of penalty factor on the final price has been examined. No other study has investigated the effect of different penalty factors for the same power system; iii) the test system with 50 generators, when considering all the constraints of the generating units, imposes significant non-linearity to the system. The convergence to the optimal solution will become cumbersome as it is the largest reported test case for solving the CEED problem.

The organisation of this study is as follows. Section 2 demonstrates the problem formulation and mathematical methods. Section 3 provides simulation results, where the effectiveness and superiority of the proposed method to solve the CEED problem has been discussed. Subsequently, the conclusion is given in Section 4.

2. PROBLEM FORMULATION

2.1 Combined Environmental Economic Dispatch (CEED)

The main objective of classical economic load dispatch (ELD) is to minimise the total cost of generation by determining the optimum scheduling of generating units and ensuring the satisfaction of system constraints. This study has divided the operation constraints into two different categories. The first category is related to the particular characteristics of the generating units such as generation capacity, the valve-point effect and environmental emission levels, while the second one is associated with physical constraints such as ramp rate limits, prohibited operating zones and spinning reserve levels.

The cost objective function of CEED can be represented by a quadratic cost function [30]:

$$f_{gc}(P_i) = \sum_{i=1}^{N_G} (a_i + b_i P_i + c_i P_i^2) \quad [\$/h] \tag{1}$$

The effect of valve-point loading can be modelled by adding a recurring rectified term to the main cost function as given in [30], where the cost function curve with the effect of valve-point loading is shown in Fig. 1:

$$f_{gc}(P_i) = \sum_{i=1}^{N_G} [(a_i + b_i P_i + c_i P_i^2) + |d_i \sin(e_i \times (P_i^{min} - P_i))|] \quad [\$/h] \tag{2}$$

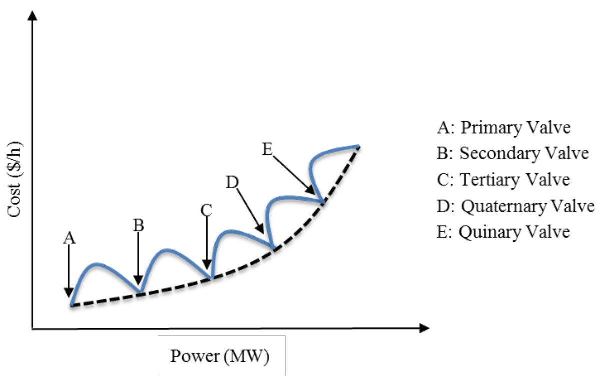


Figure 1: Fuel cost function curve for CEED with valve-point loading effect

Most thermal and fossil-based generating units are major sources of NO_x, and have been strictly advised by the environmental protection agency (EPA) to reduce their emissions. In this study, the emission of NO_x is considered to be optimally moderated from the environmental preservation point of view. The emission cost function, including the valve-point effect, can be expressed as follows [31]:

$$f_{emc}(P_i) = \sum_{i=1}^{N_G} [(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \eta_i \exp(\delta_i P_i)] \quad [lb/h] \tag{3}$$

The total generation cost of CEED as a multi-objective optimisation can be converted into a single objective function through the combination of generation cost and emission cost as well as the consideration of the price penalty factor h_i [32]:

$$F_{ct}(P_i) = f_{gc} + h_i \times f_{emc}(P_i) \tag{4}$$

$$F_{ct}(P_i) = \sum_{i=1}^{N_G} [(a_i + b_i P_i + c_i P_i^2) + |d_i \sin(e_i \times (P_i^{min} - P_i))|]$$
$$+ h_i \times \sum_{i=1}^{N_G} [(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \eta_i \exp(\delta_i P_i)] \quad [\$/h] \tag{5}$$

The proposed CEED objective function is subject to the following constraints:

Equality constraint: The total power output of the system should be capable of meeting the total load demand and power losses (I), and in the case of a lossless systems it should be able to satisfy the total load demand (II).

$$(I) \qquad \sum_{i=1}^{N_G} P_i = P_D + P_L \tag{6}$$

$$(II) \qquad \sum_{i=1}^{N_G} P_i = P_D \tag{7}$$

The power loss of the system can be determined by Korn's loss formula [33]:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{8}$$

Or re-written in matrix notation as:

$$P_L = P^T [B] P + B_0 P + B_{00} \tag{9}$$

Inequality constraint: For stable operation, all generating units are strictly constrained to operate at their minimum and maximum generation limits; consequently the inequality constraint is:

$$P_i^{min} \le P_i \le P_i^{max} \quad \text{for } i = 1, 2, 3 \ldots N_G \tag{10}$$

Ramp rate limit: conforming to [34], the inequality constraints due to ramp rate constraints for changes in generation levels are modified; (I) as generation increases and (II) as generation decreases.

$$(I) \qquad P_i - P_i^0 \le UR_i \tag{11}$$

$$(II) \qquad P_i^0 - P_i \le DR_i \tag{12}$$

By considering the inequality constraints, equations (11) and (12) can be rewritten:

$$max(P_i^{min}, P_i^0 - DR_i) \le P_i \le min(P_i^{max}, P_i^0 + UR_i) \tag{13}$$

Fig. 2 shows the mechanism of the generating units when considering the ramp rate limits.

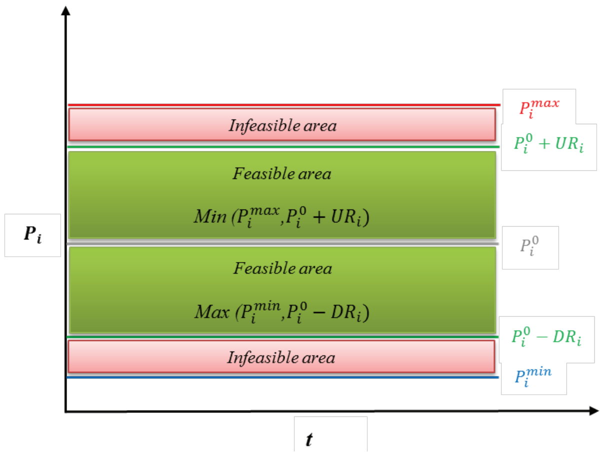


Figure 2: Operation of generating units when considering the ramp rate limits

Prohibited operating zone (POZ): the POZ is an interval in which generating units are not able to operate due to the inherent nature of thermal units that may have steam valve operation or vibrations in the shaft bearings. The principle of POZ has been depicted in Fig. 3. The feasible operating zones of unit i are described as [35]:

$$\begin{cases} P_i^{min} \le P_i \le P_{i,l}^l \\ P_{i,l}^u \le P_i \le P_{i,k}^l \\ P_{i,k}^u \le P_i \le P_{i,nz_i}^l \\ P_{i,nz_i}^u \le P_i \le P_i^{max} \end{cases} \quad \text{for } k = 1, 2, 3 \ldots nz_i \quad \forall i \notin \Omega \tag{14}$$

Spinning reserve: to have a reliable operation a minimum spinning reserve should be considered to meet the load fluctuation and unforeseen outages of the generating units and grid components [35]:

$$\sum_{i=1}^{N_G} S_i \geq S_R \tag{15}$$

Where:

$$S_i = min(P_i^{max} - P_i, S_i^{max}); \quad S_i = 0; \forall i \in \Omega \tag{16}$$

Where Ω is related to sets of units having POZs. It is significant to mention that spinning reserve will be carried out from units without POZs. Those units having no POZs are responsible for maintaining the system spinning reserve requirements which can be set as a fraction of the load demand or equal to the capacity of the largest unit [36].

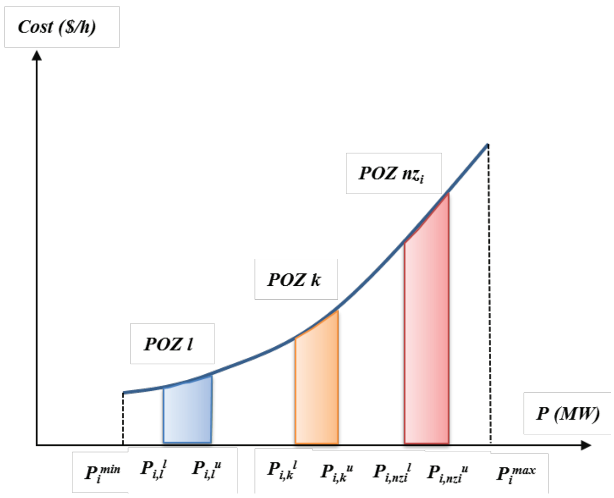


Figure 3: Fuel cost function curve with prohibited operating zones

Price penalty factors: Four different types of price penalty factors (PPFs) are proposed. PPFs describe the proportion between fuel cost and emission cost curves without considering the valve point effect. The PPFs are as follows:

Max-Max:

$$h_i^{max-max} = \frac{a_i + b_i P_i^{max} + c_i (P_i^{max})^2}{\alpha_i + \beta_i P_i^{max} + \gamma_i (P_i^{max})^2} \quad [\$/lb] \tag{17}$$

Max-Min:

$$h_i^{max-min} = \frac{a_i + b_i P_i^{max} + c_i (P_i^{max})^2}{\alpha_i + \beta_i P_i^{min} + \gamma_i (P_i^{min})^2} \quad [\$/lb] \tag{18}$$

Min-Max:

$$h_i^{min-max} = \frac{a_i + b_i P_i^{min} + c_i (P_i^{min})^2}{\alpha_i + \beta_i P_i^{max} + \gamma_i (P_i^{max})^2} \quad [\$/lb] \tag{19}$$

Max-Max:

$$h_i^{min-min} = \frac{a_i + b_i P_i^{min} + c_i (P_i^{min})^2}{\alpha_i + \beta_i P_i^{min} + \gamma_i (P_i^{min})^2} \quad [\$/lb] \tag{20}$$

The main purpose of PPFs is to convert the physical implication of the emission standard from the emission weight to the fuel cost of the emission.

2.2 *Evaluation of generation levels*

To ensure that the equality constraint of the system is always maintained, this study proposes a power balance violation (PBV) formulation to continuously satisfy the equality constraint. Equation (6) is rewritten as:

$$\sum_{i=1}^{N_G} P_i \geq P_D + P_L \tag{21}$$

by modification of equation (21), the PBV is formulated as:

$$PBV = max\left(1 - \frac{\sum_{i=1}^{N_G} P_i - P_L}{P_D}, 0\right) \tag{22}$$

As long as equation (21) is satisfied then the PBV is equal to zero. To maintain the equality constraint and find the most optimal solutions in the search space, the algorithm accepts the solutions which are able to hold the following relation:

$$P_D + P_L - \sum_{i=1}^{N_G} P_i = 0 \tag{23}$$

To accelerate the process of convergence to achieve optimal solutions, this study has used an evaluation function to push the answers of the optimisation algorithm towards the most optimum solution possible by means of a penalisation factor. The proposed method evaluation function which would be evaluated for each iteration is formulated as:

$$F_{eval} = F_{ct}(P_i) \times (1 + PF \times PBV) \tag{24}$$

In this study PF has been considered to be equal to 1000, in many practical problems, the selection of the parameters is subject to the characteristics of the problem.

2.3 *Cultural Algorithms*

The principles behind the cultural algorithm were proposed by Reynolds in 1994 [27]. CA is a type of computational intelligence algorithm which is inspired by the cultural inheritance process of several generations. The idea of this innovative optimisation technique is that culture has the potential to be emblematically encoded and shared among populations of a society [37].

The mechanism of CA is based on the discovery of an elite individual in a population, and setting the aim of the population to reach the same level as the elite's knowledge. The culture evolution of the population would improve the adaptability of the individuals towards the targeted aims and the speed of this process would be increased through guidance by the elite's knowledge.

The basic concepts of cultural algorithm: Culture is the accumulated experience and learned behaviour of a group of people which can be called the tradition of that group of people and which is maintained through generations.

CA is composed of two basic spaces: population space (to illustrate a genetic component according to Darwinian Theory) and belief space (to illustrate cultural principles) which differentiate the CAs from other evolutionary algorithms [37]. The population space represents and categorises the individuals based on their specifications in each set, while the belief space collects the knowledge obtained by individuals.

At each iteration of CA, individuals in their population space can be substituted and updated by some of their generations via a communication protocol. This process can be handled by implementing any population-based operators or any other evolutionary algorithms such as ABC, BBO, or FA [6]. The framework of CA is depicted in Fig. 4.

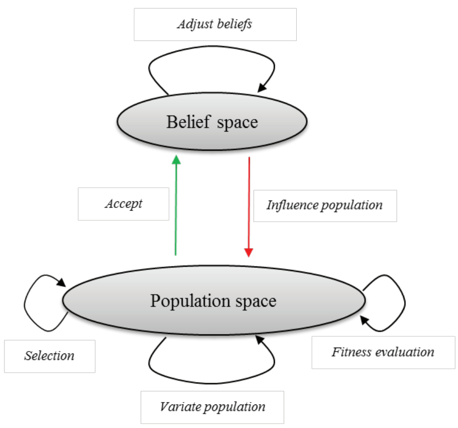


Figure 4: Illustration of conceptual framework of cultural algorithm based on the two spaces

In each generation, individuals would be evaluated by the fitness function that is determined by the evolutionary algorithm in the population space. Thereafter, an acceptance function is utilised to specify which individuals in the current population have a major influence on current beliefs.

The experience that has been acquired by accepted individuals would be applied to adjust the beliefs. Once the beliefs have been adjusted then they will be used to influence the improvement of the population. In order to vary the population space, the variation operators are responsible for using the beliefs to regulate the changes in individuals, where it is possible to use a crossover and mutation function or a self-adapting control parameter as the variation operator [38].

Belief space: comprises a set of experience and knowledge structure of the individuals. Based on Engelbrecht [38], CA is composed of four sections, such as: knowledge components, acceptance functions, belief space adjustment and influence functions.

The sections of belief space are introduced as follows:

(1) Knowledge component: The belief space stores a set of knowledge components in order to demonstrate the behavioural patterns of accepted individuals from the population space. The forms of knowledge components and representation of data structure depends on the characteristics of the problem. This study has used the vector representations to describe this component [39]. The belief space can be categorised in two knowledge components [39]:

(1.1) situational knowledge component: this component is responsible for finding the best solution in a particular period of time or a generation.

(1.2) normative knowledge component: this component provides a criterion for each individual behaviour which would be considered as a guideline for the mutational adjustment of individuals. In the process of optimisation these norms or intervals specify the suitable range that can be searched in each dimension.

The belief space can be mathematically expressed based on the definition of its components [38-39]:

$$B(t) = (S(t), N(t)) \tag{25}$$

Where:

$$S(t) = \{\hat{y}_1(t) : l = 1, 2, 3, \ldots, n_s\} \tag{26}$$

$$N(t) = (X_1(t), X_2(t), X_3(t), \ldots, X_{n_x}(t)) \tag{27}$$

For each dimension of belief space the following information is required to be saved:

$$X_j(t) = (I_j(t), L_j(t), U_j(t)) \tag{28}$$

Subject to:

$$I_j(t) = [x_j^{min}, x_j^{max}] = [l, u] \tag{29}$$

(2) Acceptance functions: To shape the beliefs in a particular population, this function decides which individuals of population will be utilised for this purpose.

Acceptance functions can be arithmetically designed in two ways [38]:

(2.1) static: n% individuals of a population will be selected.

(2.2) dynamic: by using any selection methods of evolutionary algorithms such as elitism or roulette-wheel selection.

In this study, the number of the selected individuals is determined by the following method according to [38]:

$$n_B(t) = \left[\frac{n_{tot}\gamma}{t}\right], \gamma \in [0,1] \tag{30}$$

Where:

n_B is the number of selected individuals for forming the beliefs in a population
t is the number of iterations (generation)
n_{pop} is the number of population

(3) Belief space adjustment: after selecting the number of individuals to form the beliefs, the interval of knowledge components can be updated through the following formulation [38-39]:

(3.1) Situational knowledge:

$$S(t+1) = \{\hat{y}(t+1)\} \tag{31}$$

Where:

$$\hat{y}(t+1) = \begin{cases} min_{l=1,\ldots,n_B(t)}\{X_l(t)\} & if\ f(min_{l=1,\ldots,n_B(t)}\{X_l(t)\}) \\ & < f(\hat{y}(t) \\ \hat{y}(t) & otherwise \end{cases} \tag{32}$$

(3.2) Normative knowledge:

$$x_j^{min}(t+1) = \begin{cases} x_{lj}(t) & if\ x_{lj}(t) \leq x_j^{min}(t) \\ & or f(X_l(t)) < L_j(t) \\ x_j^{min}(t) & otherwise \end{cases} \tag{33}$$

For updating $L_j(t)$:

$$L_j(t+1) = \begin{cases} f(X)l(t)) & if\ x_{lj}(t) \leq x_j^{min}(t) \\ & or f(X_l(t)) < L_j(t) \\ L_j(t) & otherwise \end{cases} \tag{34}$$

$$x_j^{max}(t+1) = \begin{cases} x_{lj}(t) & if\ x_{lj}(t) \leq x_j^{max}(t) \\ & or f(X_l(t)) < U_j(t) \\ x_j^{max}(t) & otherwise \end{cases} \tag{35}$$

For updating $U_j(t)$:

$$U_j(t+1) = \begin{cases} f(X)l(t)) & if\ x_{lj}(t) \leq x_j^{min}(t) \\ & or f(X_l(t)) < U_j(t) \\ U_j(t) & otherwise \end{cases} \tag{36}$$

Where:

$$X_l(t), l = 1,2,3\ldots,n_B(t) \tag{37}$$

(4) Influence functions: the responsibility of these functions is to influence the population space based on the adjusted beliefs in order to define the mutational step size, and the direction of change. All the CAs have the same procedure until this point, the study proposes different versions of CAs according to their influence function specifications. As mentioned in [38-39], the CAs are categorised in four different versions:

(4.1) Cultural algorithm version 1 (CA1): only the normative knowledge component is used to specify step sizes.

$$x_{ij}(t) = x_{ij}(t) + \delta_j \times N_{ij}(0,1) \tag{38}$$

Equation (37) can be rewritten as:

$$x_{ij}(t) = x_{ij}(t) + \delta_j \times N_{ij}(0,1) \tag{39}$$

Where:

$$\delta_j(t) = [x_j^{max}(t) + x_j^{min}(t)] \tag{40}$$

(4.2) Cultural algorithm version 2 (CA2): only the situational knowledge component is used to specify the direction changes. In this version of CA, we assume the strategy parameter is greater than zero ($\sigma_{ij} > 0$).

$$\acute{x}_{ij}(t) = \begin{cases} x_{ij}(t) + |\sigma_{ij}N_{ij}(0,1)| & if\ x_{ij}(t) < \hat{y}_j(t) \\ x_{ij}(t) - |\sigma_{ij}N_{ij}(0,1)| & if\ x_{ij}(t) > \hat{y}_j(t) \\ x_{ij}(t) + \sigma_{ij}N_{ij}(0,1) & otherwise \end{cases} \tag{41}$$

(4.3) Cultural algorithm version 3 (CA3): this version is the combination of both knowledge components. The situational knowledge component is used to specify the step sizes, while the normative knowledge component is used for direction changes. The definition of $\acute{x}_{ij}(t)$ will remain the same as CA2, but the strategy parameter would be redefined as:

$$\sigma_{ij}(t) = \alpha[x_j^{max}(t) + x_j^{min}(t)], 0 < \alpha < 1 \tag{42}$$

Where α denotes the ratio of the strategy parameter.

(4.4) Cultural algorithm version 4 (CA4): in the fourth version of CA, the normative knowledge component is assigned to handle the step sizes and direction changes.

$$x_{ij}(t) = \begin{cases} x_{ij}(t) + |\sigma_{ij}N_{ij}(0,1)| & if\ x_{ij}(t) < x_j^{min}(t) \\ x_{ij}(t) - |\sigma_{ij}N_{ij}(0,1)| & if\ x_{ij}(t) > x_j^{max}(t) \\ x_{ij}(t) + \beta\sigma_{ij}N_{ij}(0,1) & otherwise \end{cases} \tag{43}$$

In CA4, the scaling factor is applicable for all positive values ($\beta > 0$), and the strategy parameter can be defined as is described in CA3. In all versions of CA influence functions, subscript i denotes the individual and subscript j describes the type of the knowledge component.

3. RESULTS AND DISCUSSION

The proposed algorithms were tested on different scenarios of CEED that consider several physical constraints of generating units and system, including:

- with and without transmission loss
- with and without maintaining spinning reserve constraint
- with and without prohibited operating zones
- valve-point effect
- ramp rate limits
- fuel emission constraint
- price penalty factors

To investigate and verify the robustness of the proposed methods, they were tested on three different systems of 5, 20 and 50 generating units respectively. All methods were implemented and compared in this study to show the capability of the methodology. The codes and algorithms were developed on MATLAB 2013a to perform the case studies and executed on a personal computer with the following specifications, Intel® Core^{TM} i7-3770 (3.40 GHz), 8.00 GB RAM (DDR5) and windows 8.1 operating system.

As all the evolutionary algorithms are highly sensitive to the tuning of their decision parameters and variables, the study selected the suitable settings for all versions of CA. These parameters are population size n_{pop}, acceptance ratio P_{accept}, ratio of strategy parameter α, scaling coefficient β set to 50, 0.15, 0.25, and 0.5 respectively. To have a uniform comparison among all compared evolutionary algorithms, the spinning reserve requirement was set to 5% of total load demand as in [1]. The maximum iterations for all the trials were fixed to 300.

To validate the effectiveness of the proposed method of the study, the following case studies have been analysed and compared:

Case 1: 5 generating units; without considering POZ

Case 2: 20 generating units (four times replication of the test system of case 1); without considering power transmission losses and maintaining spinning reserve

Case 3: 50 generating units (ten times replication of the test system of case 1); without considering power transmission losses and maintaining spinning reserve

3.1 Case 1

A small test system comprising of 5 generating units was considered based on [40–42] with a minor modification of the test system. The system specifications are given in Table (1), (2) and (3). The loss coefficients (B-coefficients) of the transmission network are given in Table (4), where the values are expressed in p.u. on a 100 MVA base. Table 1 lists the physical operating limits and cost coefficients of generating units such as quadratic cost, proportional cost and fixed cost. Table 2 lists the ramping limits as well as the quantitative information of the prohibited zones for the generating units. Table 3 lists a detailed associated emission cost for the NOx through its respective coefficients costs. The valve-point effect, ramp rate limits, spinning reserve requirement, emission constraints and the effect of price penalty factors (PPFs) on the total generation cost were considered for the study. The total load demand of the test system was 730 MW. In this case, 100 trials have been carried out for the purpose of producing the results.

The convergence processes of the proposed algorithm with different PPFs are shown in Fig 6 (a, b, c and d) where the total cost is plotted against the number of iterations. The obtained results are compared with BBO, ACOR, ABC, PSO, GA, the combination of GA and PSO (GAPSO), FA. Fig. 6.a shows the convergence process with Max-Max PPF. As shown, CA3 has the second highest initial guess, however it reaches its optimum level in less than 50 iterations with the last step of reduction occurring at the 50th iteration with a best minimum cost of 2039.46 ($/h). In terms of the convergence process, most of the algorithms have reached their optimum level after the 50th iteration, with BBO only succeeding in reach to the final iteration at close to the 250th iteration.

By analysing Fig. 6(a, b, c and d), it can be seen that the proposed method is the most capable technique to find the best solution where its best obtained cost is at Min-Max PPF at 2039.17 ($/h). It is noticeable for all PPFs cases, the proposed method has achieved the final optimisation stage in less than 70 iterations, which indicates the convergence speed of the proposed method. The maximum cost, average cost, minimum cost and average elapsed time for the proposed method and other methods are shown in Table (5). For ease of comparison, the elapsed time of each method is evaluated as an average. From Table (5), it is evident that the proposed method has achieved the lowest average time and minimum total generation cost with respect to all PPFs cases among all the other methods. The most optimum average cost was achieved by CA3 through Min-Max PPF at 2042.5414 ($/h), where the average elapsed time was 2.4571 seconds.

The breakdown of generator schedules is given in Table (6). The best solution in the solution space is shown in Figure (5), where the best solution is the solution that has the lowest total cost and lowest emission cost without violating any physical constraint.

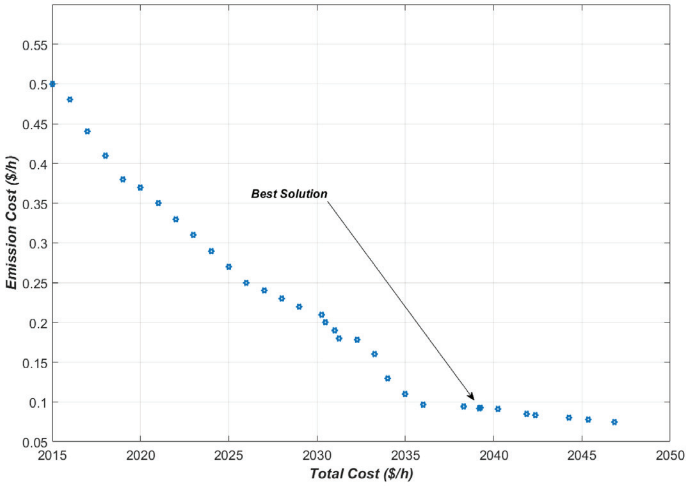


Figure 5: Best obtained solution in the solution space for case 1

Table 1: Cost coefficients and physical operating limits of generating units

Unit	a_i $(\$/h)$	b_i $(\$/MWh)$	c_i $\$/(MW)^2h$	d_i $(\$/h)$	e_i $(1/MW)$	P_i^{min} (MW)	P_i^{max} (MW)
1	25	2	0.008	100	0.042	10	75
2	60	1.8	0.003	140	0.04	20	125
3	100	2.1	0.0012	160	0.038	30	175
4	120	2	0.001	180	0.037	40	250
5	40	1.8	0.0015	200	0.035	50	300

Table 2: Ramp rate limits and POZ information of generating units

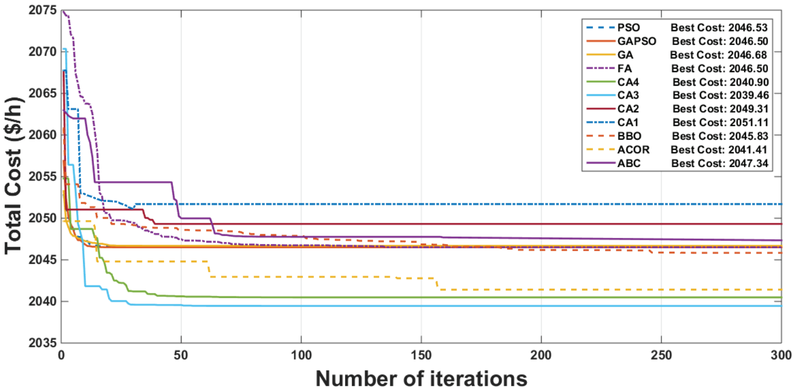
Unit	P_i^0 (MW)	UR_i (MW)	DR_i (MW)	POZ_i (MW)
1	70	30	30	[60 65]
2	100	30	30	[70 75]
3	150	40	40	[120 125]
4	110	50	50	[80 90]
5	270	50	50	[230 240]

Table 3: Emission curve coefficients of generating units

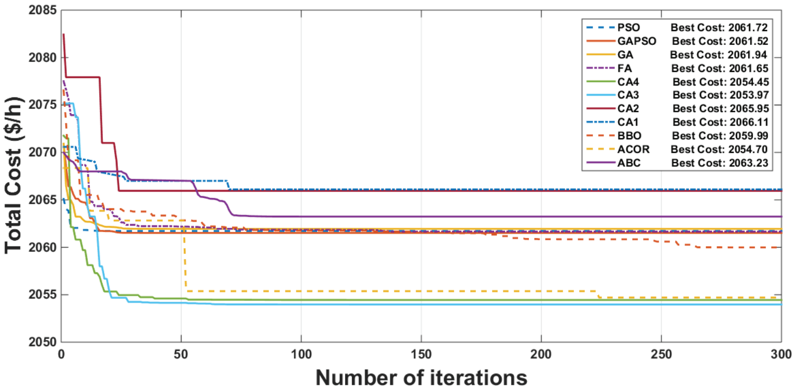
Unit	α_i (lb/h)	β_i (lb/MWh)	γ_i $lb/(MWh)^2h$	η_i (lb/h)	δ_i $(1/MW)$
1	80	-0.805	0.018	0.655	0.02846
2	50	-0.555	0.015	0.5773	0.02446
3	60	-1.355	0.0105	0.4968	0.0227
4	45	-0.6	0.008	0.486	0.01948
5	30	-0.555	0.012	0.5053	0.02075

Table 4: The transmission loss coefficients

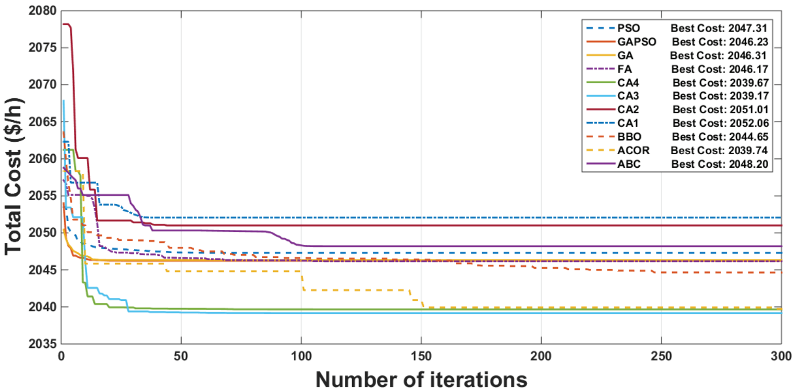
	0.000049	0.000014	0.000015	0.000015	0.000020
	0.000014	0.000045	0.000016	0.00002	0.000018
B	0.000015	0.000016	0.000039	0.000010	0.000012
	0.000015	0.000020	0.000010	0.000040	0.000014
	0.000020	0.000018	0.000012	0.000014	0.000035



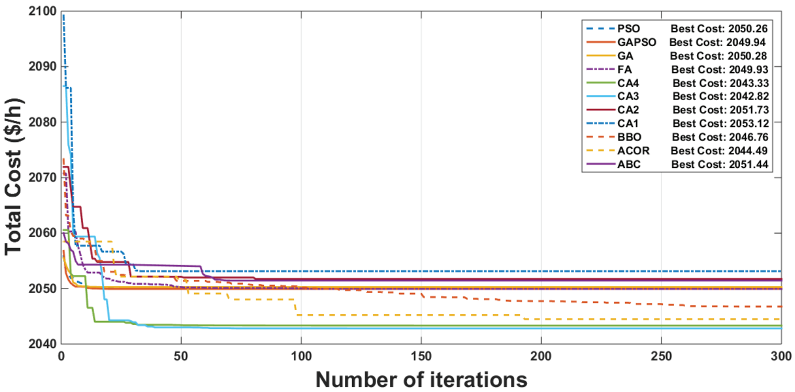
(a) Max-Max PPF



(b) Max-Min PPF



(c) Min-Max PPF



(d) Min-Min PPF

Figure 6: Convergence process of CEED cost (5 generating units)

Table 5: Comparison of the obtained results for case 1

5 Units System		Max Cost	Avg Cost	Min Cost	Avg Elapsed Time (s)
BBO	Max Max	2054.5656	2047.5029	2045.8321	8.4732
	Max Min	2065.2573	2061.2359	2059.9912	
	Min Max	2050.3511	2046.0231	2044.6514	
	Min Min	2052.2072	2049.5228	2046.7632	
ACOR	Max Max	2305.1833	2067.3245	2041.4102	6.2199
	Max Min	2167.204	2057.1314	2054.7065	
	Min Max	2187.797	2049.3181	2039.7443	
	Min Min	2144.6517	2049.8958	2044.4932	
FA	Max Max	2047.8929	2046.2479	2046.5098	2.8594
	Max Min	2062.8454	2061.1854	2061.6578	
	Min Max	2047.8448	2045.8421	2046.1733	
	Min Min	2051.3145	2049.3753	2049.9321	
GAPSO	Max Max	2049.5923	2047.374	2046.5013	23.2906
	Max Min	2063.0634	2062.4204	2061.5215	
	Min Max	2049.798	2047.1124	2046.2341	
	Min Min	2051.9561	2050.6466	2049.9444	
PSO	Max Max	2049.7785	2047.5568	2046.5321	4.2648
	Max Min	2063.3545	2062.5546	2061.7235	
	Min Max	2049.8845	2047.3345	2047.3121	
	Min Min	2051.9623	2050.7465	2050.2632	
GA	Max Max	2049.8701	2048.0021	2046.6845	5.4049
	Max Min	2063.4025	2062.6801	2061.9432	
	Min Max	2050.1478	2047.7468	2046.3145	
	Min Min	2051.8845	2050.8865	2050.2842	
ABC	Max Max	2049.9904	2049.9879	2047.3458	6.3695
	Max Min	2064.6541	2062.8788	2063.23	
	Min Max	2050.7456	2048.4563	2048.2032	
	Min Min	2052.3545	2051.0002	2051.4433	
CA1	Max Max	2061.4022	2053.9172	2051.1125	1.2386
	Max Min	2081.2015	2068.8055	2066.1124	
	Min Max	2061.2573	2053.1706	2052.0645	
	Min Min	2065.9603	2056.1002	2053.1237	
CA2	Max Max	2061.8546	2053.9832	2049.3154	1.2594
	Max Min	2081.5487	2069.0458	2065.9541	
	Min Max	2061.7568	2054.0001	2051.0123	
	Min Min	2066.1254	2056.7453	2051.7311	
CA3	Max Max	2053.7469	2042.1457	2039.4621	1.3578
	Max Min	2063.6157	2056.2873	2053.9714	
	Min Max	2055.5814	2042.5414	2039.1724	
	Min Min	2056.2588	2045.6611	2042.8214	
CA4	Max Max	2053.8546	2042.5436	2040.9012	1.3281
	Max Min	2063.7654	2057.021	2054.4532	
	Min Max	2056.3254	2042.8547	2039.6714	
	Min Min	2056.5487	2045.8745	2043.3302	

Table 6: The best obtained solutions of the proposed method (CA3) for case 1

No. of units	1	2	3	4	5
Schedule (MW)	32.2494	108.7979	161.0268	226.8128	212.3711
Generation Cost ($/h)	97.8191	291.3472	469.2718	625.0697	489.9202
Valve-point Cost ($/h)	1.6309	8.6734	13.8865	21.6623	19.8049
Emission Cost ($/h)	0.0076	0.0218	0.0119	0.026	0.0247
Total Cost ($/h)			2039.178		
Ploss (MW)			11.258		

3.2 Case 2

In order to demonstrate the robustness of the proposed method on a larger test system, the proposed method was applied to a 20 unit system. All the physical constraints of generating units as described in case 1 (aside from the spinning reserve requirement) as well as the effect of POZs were considered in this case. The total load demand was 2920 MW. In this case, transmission line losses were neglected. To have the refinement process 100 runs have been performed for each method. The comparison between the proposed method and the other evolutionary algorithms during the convergence process with the consideration of their PPFs are depicted in Fig 8 (a, b, c and d).

It is clear from Fig 8 (a, b, c and d) that the proposed method provides the lowest cost among the other methods in all cases. The convergence process has been extended in all methods due to the enlargement of the test system; nevertheless the proposed method has converged in less than 100 iterations which indicates its effectiveness. It is noticeable that the Min-Max and Min-Min PPFs provide the lowest and highest total generation cost for the proposed method with costs of 8057.23 and 8070.21 ($/h) respectively. The detailed results of 20 unit system with respect to all PPFs are shown in Table (7). It is clear that the proposed method obtained the lowest generation cost when compared to other techniques, where the minimum average cost was computed by its Min-Max PPF to be 8062.7931 ($/h). It is significant to mention that even by enlarging the test system where the degrees of non-convexity and non-linearity of the problem were significantly increased, the proposed method managed to maintain a fast run time and its efficiency where the difference by the previous case is only 1.0993 s. The proposed method in comparison to the other versions of cultural algorithm has a slightly longer time to converge as it is using both knowledge components (situational and normative) for its influence function. Figure (7) illustrates the best obtained solution in the solution space where the best solution is the solution that has the lowest total cost and lowest emission cost without violating any physical constraint. Table (8) lists the best solution detailed information for generator schedules and their associated costs.

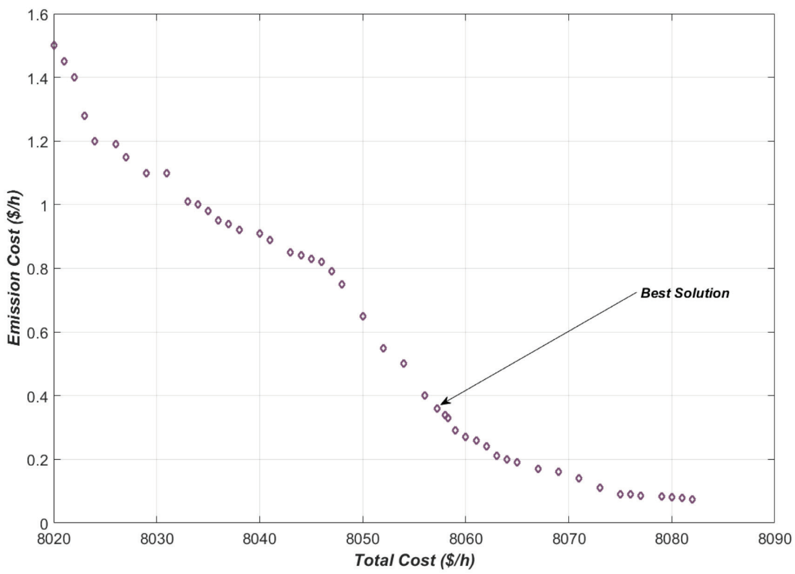
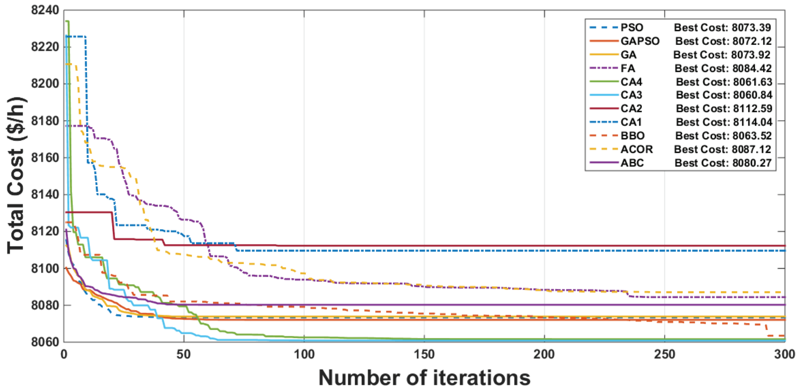
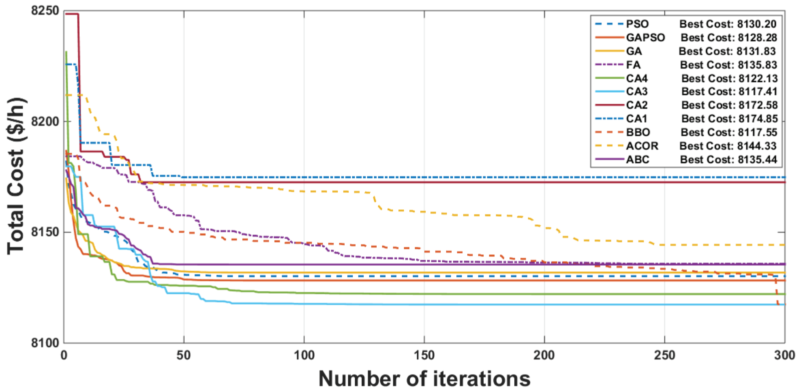


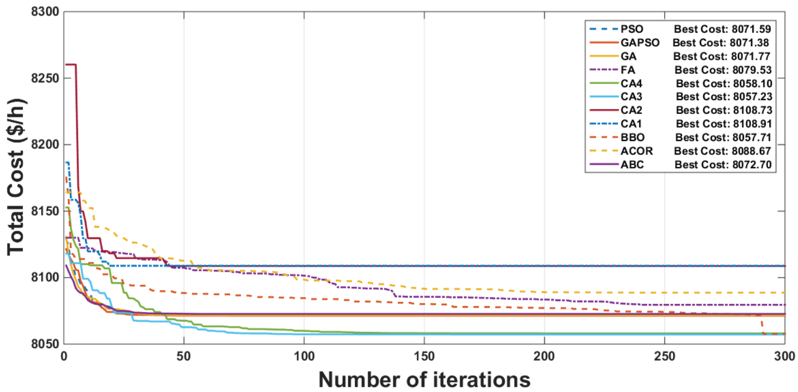
Figure 7: Best obtained solution in the solution space for case 2



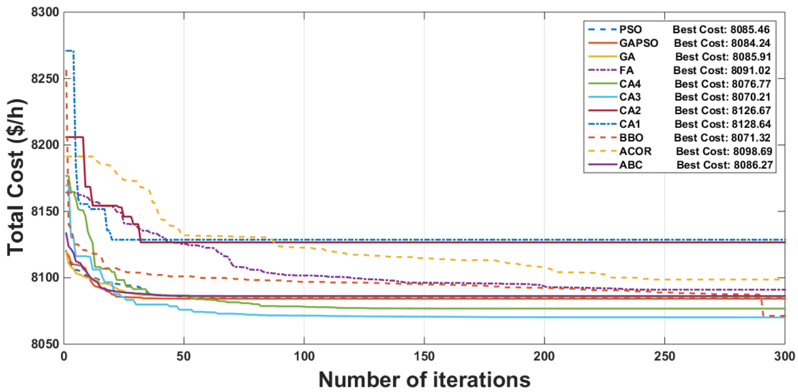
(a) Max-Max PPF



(b) Max-Min PPF



(c) Min-Max PPF



(d) Min-Min PPF

Figure 8: Convergence process of CEED cost (20 generating units)

Table 7: Comparison of the obtained results for case 2

20 Units System		Max Cost	Avg Cost	Min Cost	Avg Elapsed Time (s)
BBO	Max Max	8098.153	8074.88	8063.5204	24.3705
	Max Min	8144.5893	8132.983	8117.5522	
	Min Max	8090.8475	8073.56	8057.7132	
	Min Min	8103.9127	8089.66	8071.3245	
ACOR	Max Max	8111.0125	8095.4521	8087.1253	15.2124
	Max Min	8201.5435	8185.4565	8144.3356	
	Min Max	8225.5423	8100.0204	8088.6745	
	Min Min	8254.8457	8116.1024	8098.6974	
FA	Max Max	8104.181	8083.8803	8084.4253	2.8965
	Max Min	8171.9771	8142.0902	8135.8323	
	Min Max	8100.926	8082.7155	8079.5345	
	Min Min	8129.6365	8098.029	8091.0254	
GAPSO	Max Max	8083.9209	8073.9642	8072.1245	29.0153
	Max Min	8141.7844	8131.5726	8128.2845	
	Min Max	8083.1013	8072.2043	8071.3847	
	Min Min	8093.1127	8085.701	8084.2456	
PSO	Max Max	8101.2544	8088.4521	8073.5412	8.4742
	Max Min	8145.5478	8134.8542	8130.2045	
	Min Max	8090.6545	8086.7546	8071.5942	
	Min Min	8125.6587	8097.5687	8085.4675	
GA	Max Max	8107.8542	8089.4574	8073.9245	9.5049
	Max Min	8187.5687	8135.8765	8131.8345	
	Min Max	8100.2548	8088.5544	8071.7745	
	Min Min	8145.6578	8101.2587	8085.9175	
ABC	Max Max	8212.45	8100.4525	8080.2745	13.4197
	Max Min	8275.3587	8175.6547	8135.4457	
	Min Max	8212.5435	8111.5478	8072.7065	
	Min Min	8346.5435	8101.4587	8086.2745	
CA1	Max Max	8188.5478	8135.4578	8114.0423	2.1535
	Max Min	8254.5478	8178.7723	8174.8545	
	Min Max	8145.8528	8122.7744	8108.9147	
	Min Min	8185.9874	8150.5547	8128.6475	
CA2	Max Max	8133.5874	8117.5153	8112.5954	2.3326
	Max Min	8194.3054	8175.8547	8172.5874	
	Min Max	8134.3103	8109.3466	8108.7387	
	Min Min	8150.7771	8128.0509	8126.6787	
CA3	Max Max	8104.6353	8067.5709	8060.8475	2.4571
	Max Min	8158.7169	8118.3626	8117.4178	
	Min Max	8102.5586	8062.7931	8057.2354	
	Min Min	8113.2448	8074.6219	8070.2145	
CA4	Max Max	8104.7854	8079.8745	8061.6354	2.4003
	Max Min	8167.5841	8137.8745	8122.7854	
	Min Max	8103.0124	8078.4658	8058.1088	
	Min Min	8113.4521	8095.5478	8076.7754	

Table 8: The best obtained solutions of the proposed method (CA3) for case 2

No. of units	Schedule (MW)	Generation Cost ($/h)	Valve-point Cost ($/h)	Emission Cost ($/h)
1	56.2537	162.8232	3.3899	0.0097
2	108.0018	289.3965	8.5958	0.0215
3	167.0662	484.3324	14.5249	0.0133
4	192.4141	541.8513	17.6879	0.0177
5	240	558.4	23.1608	0.0327
6	34.8082	104.3093	1.8184	0.0077
7	104.7494	281.4661	8.2784	0.0204
8	140.8305	419.544	11.7503	0.008
9	228.4784	629.1591	21.8545	0.0263
10	240.6657	560.0783	23.2416	0.033
11	43.9795	128.4326	2.4906	0.0083
12	104.1066	279.9063	8.2157	0.0202
13	151.0329	444.5421	12.8297	0.0098
14	183.0794	519.6769	16.6077	0.0158
15	252.4492	590.0045	24.6708	0.0371
16	32.08	97.3929	1.6185	0.0076
17	116.6018	310.6711	9.4345	0.0248
18	137.1604	410.6125	11.3619	0.0074
19	180.1106	512.661	16.2641	0.0152
20	206.1316	474.7726	19.0462	0.0229
Total Cost ($/h)		8057.2343		

3.3 Case 3

To verify the capability of the proposed method with greater complexity and non-convexity, the method has been tested on a 50 unit system, which is the largest test system that considers all the physical constraints of the generating units found in literature. The total demand for the system is equal to 7300 MW. Fig 10 (a, b, c and d) represent the convergence process of optimisation, where the study was successfully employed and the obtained results show the effectiveness of CA3 in finding the most optimum solution in all the considered PFFs cases. By increasing the complexity of the solution, CA3 has been able to acquire the lowest cost solution as well as reaching the final value of the convergence process in almost 100 iterations in most cases. The minimum total cost obtained by CA3 through Min-Max PPF is 20181.96 (\$/h).

The details of the solutions are found in the Table (9), where CA3 has acquired the lowest total generation costs in comparison to the other methods. As is seen, all the versions of CA are fairly fast in terms of convergence while CA3 is the most robust and fastest algorithm in finding the most optimal solution. The second algorithm which has almost the same time to convergence is FA, however from the results it is obvious that FA is not as capable as CA3 in terms of computation efficiency and convergence. In this case the best average cost has been obtained by the proposed method of the study (CA3) at 20190.2474 (\$/h) within 3.7235 seconds

Detailed information regarding the best solution generator schedules and associated costs is listed in Table (10). Fig (9) illustrates the best solution in the solution space, where the best solution is the solution that has the lowest total cost and lowest emission cost without violating any physical constraint.

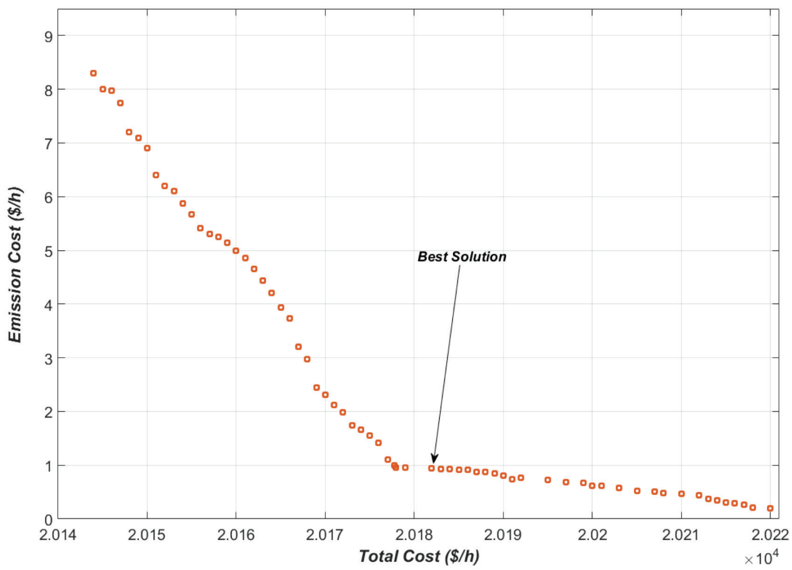
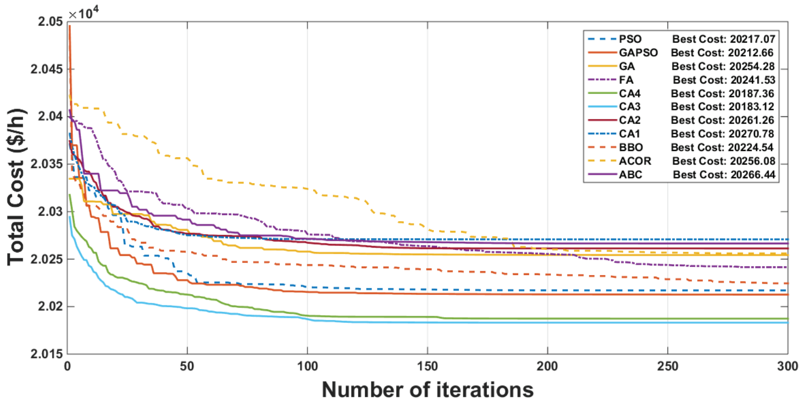
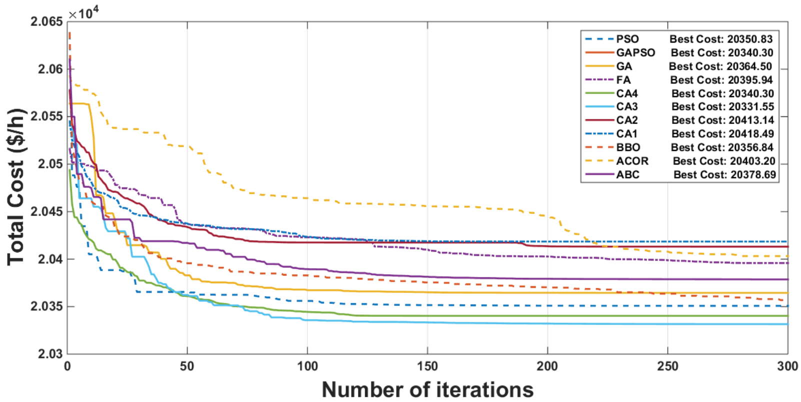


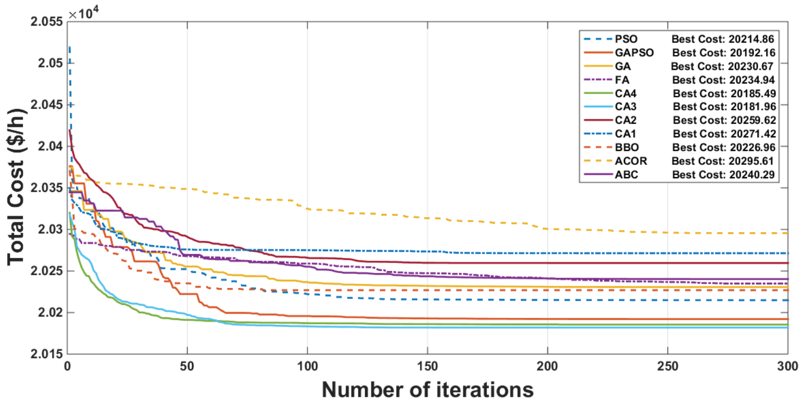
Figure 9: Best obtained solution in the solution space for case 3



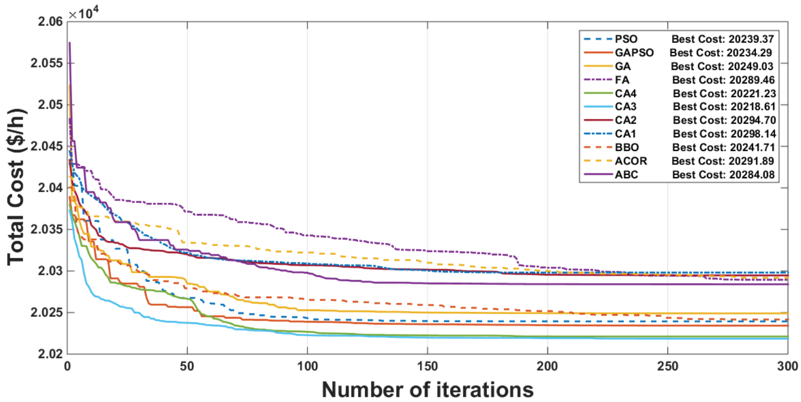
(a) Max-Max PPF



(b) Max-Min PPF



(c) Min-Max PPF



(d) Min-Min PPF

Figure 10: Convergence process of CEED cost (50 generating units)

Table 9: Comparison of the obtained results for case 3

50 Units System		Max Cost	Avg Cost	Min Cost	Avg Elapsed Time (s)
BBO	Max Max	20486.2304	20245.0990	20224.5400	49.4478
	Max Min	20637.9955	20383.5605	20356.8399	
	Min Max	20370.6733	20233.6180	20226.9600	
	Min Min	20400.5471	20264.9528	20241.7100	
ACOR	Max Max	20422.1366	20301.0561	20256.0804	23.4582
	Max Min	20592.5007	20459.5694	20403.2000	
	Min Max	20374.6079	20319.3026	20295.6132	
	Min Min	20413.5235	20316.6638	20291.8900	
FA	Max Max	20399.4607	20274.9511	20241.5302	3.2163
	Max Min	20516.1290	20420.7332	20395.9400	
	Min Max	20294.6761	20251.9225	20234.9412	
	Min Min	20482.8795	20332.3212	20289.4600	
GAPSO	Max Max	20495.4164	20223.9754	20212.6601	48.1425
	Max Min	20493.7161	20351.2567	20340.2991	
	Min Max	20376.1368	20209.1629	20192.1619	
	Min Min	20388.8804	20246.6771	20234.2913	
PSO	Max Max	20370.6965	20229.7232	20217.0722	14.2585
	Max Min	20637.1721	20360.1736	20350.8318	
	Min Max	20519.0375	20231.8353	20214.8612	
	Min Min	20428.6969	20255.4949	20239.3713	
GA	Max Max	20334.6094	20263.9854	20254.2839	16.1012
	Max Min	20563.8023	20380.1259	20364.5017	
	Min Max	20346.2926	20244.1745	20230.6732	
	Min Min	20384.2346	20263.2494	20249.0332	
ABC	Max Max	20406.7888	20277.9392	20266.4438	20.3574
	Max Min	20610.1221	20395.0305	20378.6912	
	Min Max	20344.7634	20257.7363	20240.2925	
	Min Min	20574.4659	20303.0045	20284.0838	
CA1	Max Max	20382.1294	20276.4824	20270.7821	3.0765
	Max Min	20545.0166	20428.1621	20418.4901	
	Min Max	20349.7902	20276.4795	20271.4176	
	Min Min	20444.1817	20312.4488	20298.1400	
CA2	Max Max	20374.2832	20271.1612	20261.2616	3.5132
	Max Min	20577.7849	20425.5726	20413.1428	
	Min Max	20419.3395	20274.1327	20259.6235	
	Min Min	20433.4961	20307.4231	20294.6977	
CA3	Max Max	20294.3789	20190.7251	20183.1180	3.7235
	Max Min	20540.3924	20349.5904	20331.5500	
	Min Max	20318.4603	20190.2474	20181.9615	
	Min Min	20373.0573	20228.6551	20218.6160	
CA4	Max Max	20317.6973	20198.0954	20187.3556	3.5257
	Max Min	20493.7161	20351.2567	20340.2991	
	Min Max	20320.1584	20191.5621	20185.4861	
	Min Min	20379.9107	20236.2923	20221.2304	

Table 10: The best obtained solutions of the proposed method (CA3) for case 3

No. of units	Schedule (MW)	Generation Cost ($/h)	Valve-point Cost ($/h)	Emission Cost ($/h)
1	40	117.8	2.1989	0.008
2	116.6705	310.8429	9.4413	0.0248
3	160.6625	468.3663	13.848	0.0118
4	158.3568	461.7905	13.7443	0.0116
5	252.9479	591.2801	24.7313	0.0373
6	40	117.8	2.1989	0.008
7	109.7629	293.7169	8.7675	0.0222
8	162.3045	472.4507	14.0216	0.0122
9	159.8847	465.3326	13.9214	0.0118
10	251.3998	587.3225	24.5436	0.0367
11	40.0138	117.8364	2.1999	0.008
12	120.2852	319.9189	9.7937	0.0263
13	170.6043	493.1961	14.8988	0.0141
14	160	465.6	13.9347	0.0118
15	252.774	590.8353	24.7102	0.0372
16	43.5479	127.2671	2.4589	0.0083
17	121.2372	322.3225	9.8865	0.0267
18	160.9754	469.1442	13.8811	0.0119
19	159.0099	463.304	13.82	0.0117
20	245.9009	573.3225	23.8767	0.0348
21	40.1514	118.1998	2.21	0.008
22	112.1372	299.5711	8.9991	0.0231
23	162.0619	471.847	13.996	0.0121
24	159.883	465.3285	13.9212	0.0118
25	265.3076	623.1359	26.229	0.0422
26	40.222	118.3864	2.2152	0.008
27	114.4183	305.2277	9.2216	0.0239
28	135.2949	406.0849	11.1644	0.0071
29	160	465.6	13.9347	0.0118
30	271.1008	638.2249	26.9305	0.0446
31	40.2503	118.4613	2.2173	0.008
32	119.811	318.7238	9.7475	0.0261
33	164.7089	478.4434	14.2758	0.0127
34	159.9998	465.5995	13.9347	0.0118
35	266.2775	625.655	26.3465	0.0426
36	40.4806	119.0706	2.2342	0.008
37	122.9967	326.7787	10.0581	0.0274
38	147.5973	436.0962	12.4663	0.0092
39	156.0101	456.3594	13.4723	0.0112
40	240	558.4	23.1608	0.0327
41	42.303	123.9223	2.3677	0.0082
42	108.4978	290.6113	8.6441	0.0217
43	154.0886	452.0781	13.1529	0.0104
44	159.9994	465.5986	13.9346	0.0118
45	240	558.4	23.1608	0.0327
46	40	117.8	2.1989	0.008
47	118.785	316.1426	9.6474	0.0257
48	164.2809	477.3758	14.2305	0.0126
49	160	465.6	13.9347	0.0118
50	266.9978	627.5278	26.4337	0.0429
Total Cost ($/h)		20181.9612		

4. CONCLUSION

Four different versions of CA have been proposed to solve the CEED problem while the main emphasis of emission reduction is focused on the NO_x gases. The proposed method employed the two knowledge components of the belief space to characterise the versions of the CA. To enhance the performance of the proposed algorithms, various sophisticated and highly efficient influence functions based on that of mixture situational and normative knowledge component were applied to the CA versions to find the optimal solution in the complex non-linear problem of CEED. In order to validate the effectiveness of the proposed method, different test cases (5, 20 and 50 units system) with the inclusion of network and physical constraints of generating units such as the valve-point effect, emission constraints, the ramp rate limits and the prohibited zones have been studied. To maintain the equality and inequality constraints of CEED, an effective and simple function handle was introduced to find the feasible space and escape local optima. The multi-objective CEED problem has been converted to a single objective problem through four types of PPFs to investigate the precise effects of emission levels on the total generation costs. The simulation results demonstrate the superiority of the CA3 in achieving the best possible solution in a fast computation time in comparison with the other methods in all the test cases. This is a considerable feature for large-scale power systems. The results conclude that Min-Max price penalty factor yields a noticeably lower total generation cost for CEED among all the studied cases of PPFs.

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