ءءUNIVERSITE KASDI MERBAH OUARGLA

Faculté des Sciences Appliquées

Département de Génie Electrique

Mémoire

MASTER ACADEMIQUE

Domaine : Sciences et technologies

Filière : Electrotechnique

Spécialité : Réseaux électriques

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Thème :

Multi-objective Optimization algorithm to solve combined Economics Emission Dispatch

Soutenu publiquement le : 14/06/2023

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Année universitaire 2022/2023.

Thanks

As a preamble to this dissertation, we thank ALLAH who helps us and gives us patience and courage during these years of language study.

We would like to express our sincere thanks to Dr.Boudjella Houari, who, as moderator of this thesis, has always been attentive throughout the writing of this thesis, as well as the inspiration, the help and the time she was kind enough to consecrate us and without whom these notes would not have seen the light of day.

I would also like to warmly thank all the teachers of the University of Kasdi Merbah and in particular those of the electrical engineering department for these encouragements as well as to the members of

jury, to Mrs. ·Larouci Benyakhlef and Boukaroura Abdelkader, who have done us the honor of accepting to judge this modest work and of having taken upon themselves the responsibility of examining and noting the fruit of our efforts .

Finally, I address a special thought to my parents for their support in my choices and their unfailing attention, as well as to my good mother, whose encouragement and unconditional love have always accompanied me.

Finally, To all those who have contributed directly or indirectly to the realization of this graduation project.

Dedications

I dedicate this modest work:

To the reason for my existence in life, and to the one who gave me kindness and tenderness, my dear mother,

To the one who spares no effort in my upbringing and upbringing,

AND To the one who taught me honesty and autonomy, my dear father, to all the members of my family and to whom the destinies wish to reunite me,

To all students in electrical engineering, in particular the branch of Réseaux électriques Promotion 2022/2023

MERABET AYMEN

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GUERMIT MED ADEL

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General Introduction

The dynamic load and emission dispatch in daily cycles is an important problem in power supply-demand management. In this problem, the goal is to meet energy demand at the lowest possible cost and with the lowest possible environmental impact due to power generation.

Multi-objective optimization algorithms are valuable tools for addressing the challenge of reducing the combined economic distribution of emissions in power systems. These algorithms consider multiple conflicting objectives simultaneously and aim to find a set of trade-off solutions that balance economic cost and emission reduction.

Multi-objective optimization algorithms play a crucial role in addressing the combined economic distribution of emissions in various industries and sectors. This problem involves the simultaneous optimization of conflicting objectives, namely minimizing economic costs and reducing emissions.**[1]**

The primary aim of these algorithms is to find a set of solutions that represent the trade-off between economic costs and emission reduction. These solutions, known as Pareto optimal solutions, cannot be improved in one objective without sacrificing performance in another. They provide decision-makers with a range of options that balance economic considerations with environmental sustainability. **[1]**

Multi-objective optimization algorithms adopt different strategies to explore the trade-off space effectively. Some commonly used algorithms include:

Genetic Algorithms (GA): GA mimics the principles of natural selection and evolution to search for optimal solutions. It operates on a population of candidate solutions, applying genetic operators such as crossover and mutation to produce new offspring. The solutions that survive and reproduce over generations represent the trade-off between economic costs and emissions.

Particle Swarm Optimization (PSO): PSO simulates the movement of particles in a multidimensional search space. Each particle represents a potential solution, and its position corresponds to the objective values. PSO adjusts the particles' velocities based on their own historical best positions and the global best position in the swarm, enabling the exploration of the trade-off space. .**[1]**

Evolutionary Algorithms (EA): EA encompasses a range of optimization algorithms inspired by natural evolution. It includes variations of genetic algorithms, evolution strategies, and genetic programming. These algorithms operate on populations of solutions, applying evolutionary operators to improve the fitness of individuals. They are effective in exploring the trade-off between economic costs and emissions.

Multi-Objective Particle Swarm Optimization (MOPSO): MOPSO extends the traditional PSO algorithm by considering multiple objectives. It maintains a diverse population of particles representing the Pareto front. Through the interactions between particles, MOPSO allows for the discovery of trade-off solutions between economic costs and emissions.

Non-dominated Sorting Genetic Algorithm II (NSGA-II): NSGA-II is a widely used multi-objective optimization algorithm. It utilizes non-dominated sorting to classify solutions into Pareto fronts based on dominance relationships. It maintains diversity among solutions using concepts like crowding distance. NSGA-II efficiently explores the trade-off between economic costs and emissions. .**[1]**

These algorithms, along with other state-of-the-art techniques, enable decision-makers to explore and evaluate a range of optimal solutions for the combined economic distribution of emissions. By considering the trade-offs between economic costs and emissions, organizations can make informed decisions that strike a balance between financial considerations and environmental impact. Ultimately, multi-objective optimization algorithms contribute to sustainable and efficient practices across various industries. .**[1]**

Chapter I: Problem Statement

I.1 Introduction

The ED problem solution aims to minimize the cost of generation of electric power through optimal adjustment of the committed generating unit outputs, while at the same time satisfying all unit and system constraints. When the environmental concerns are combined with the ED, then the problem becomes a combined economic and emission dispatch (CEED) problem.

Over the last two decades, many studies on evolutionary algorithms (EAs) have revealed that they are efficiently used to solve the multi-objective optimization problem (MOOP). Since these algorithms are population-based methods, they give multiple Pareto-optimal solutions in a single run. Since the objectives are in conflict with each other in MOOP, it is natural to attain a solution set rather than single solution. Power system decision makers can select the desired solution between them by applying the fuzzy decision-making method [1].The CEED problem description and formulation are presented in this chapter. **[2]**

In this research a multi-objective Imperialist Competitive Algorithm (MOICA) is applied for Environmental and Economic Power Dispatch (EED) problem. Due to the environmental concerns that arise from the emissions produced via fossil-fueled electric power plants, the classical economic dispatch, which operates electric power systems so as to minimize only the total fuel cost, can no longer be considered alone. Hence, by environmental dispatch, emissions can be reduced by dispatch of power generation to minimize emissions. Also, power generated, system loads, fuel cost and emission coefficients are subjected to inaccuracies and uncertainties in real-world situations. The proposed technique has been carried out on the IEEE 30-bus and 118-bus test system. The results demonstrate the capability of the proposed MOICA approach to solve of multi-objective EED problem. The comparison reported results with MODE and other techniques reveals the superiority of the proposed MOICA approach and confirms its potential for solving others.

I.2.Problem Description

As mentioned earlier, in EED problem, it is aimed to optimize both economic and environmental objectives simultaneous. This problem is formed from objective functions along with a number of equality and inequality constraints, which make the EED problem a complex optimization problem. The whole problem can be described briefly as follow:

$$Min\left(FC(P_i), E(P_i)\right) \tag{I.1}$$

$$s.t.: g(P_i) = 0, \mathrm{h}\,(P_i) \le 0$$

The fuel cost is formed from a quadratic term and a sinusoidal term which is related to valve-point loading. As mentioned in **[3]** considering valve-point loading makes EED solution more accurate and practical.

I.2.1Economic load dispatch (ELD)

The objective function of the ELD problem is minimizing the fuel cost for a specified load demand while satisfying various system and unit constraints. The fuel cost of thermal power plant scan be approximately modeled as a quadratic function of the generators output power as given in (I.2)**[4]**.

$$FC(P_i) = \sum_{i=1}^{n}(a_i P_i^2 + b_i P_i + c_i) \tag{I.2}$$

where FC is the total fuel cost of generations (\$/h), a_i, b_i, and$c_i$arethe fuel costcoefficients of the i^{th} unit, P_i is the real power on the i^{th}generator of the MW unit, and $n$is the number of generation units.

I.2.2 Equality constraints

In load dispatching, the system power balance, which is presented in (I.3), should be satisfied.

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{I.3}$$

Where P_D is the total load demand, and P_L is the total power losses in MW which can be expressed as a function of the units output power and Bloss coefficients as presented in (I.4)**[5]**.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{j=1}^{n} B_{0j} P_i + B_{00} \tag{I.4}$$

Where P_j is the real power on the j^{th}generator of the MW unit, B_{ij} is the Power transmission losses between the $i^{th}$and j^{th}generating units in MW are represented by coefficients.

I.2.3 Capacity limitations

There is a practical range for the minimum and maximum of the electrical output power of each unit as shown in (I.5).

$$P_i^{min} \leq P_i \leq P_i^{max} i = 1, 2, \cdots n \tag{I.5}$$

I.2.4 Valve point loading for cost-effective load dispatch

When the valve is not entirely opened, the impact of the valve point is enormous, and when the valve is fully opened, the impact is minimal **[6]**. This behavior can be mimicked in the characteristic curve by combining a multiple routine sinusoidal curve with a regular quadratic value feature. As a result, the generator devices' real input-output curves are non convex. There will also be ripples in the gasoline price curve when the valve begins to establish/final and will burst off when the valve is fully opened. The objective function will become when the valve point-impact is added.

The fuel cost function considering valve-point loading scan be expressed as (I.6)

$$FC(P_i) = \sum_{i=1}^{n} [(a_i P_i^2 + b_i P_i + c_i) + \left| e_i * \sin(f_i * (P_i^{min} - P_i)) \right|] \tag{I.6}$$

Where FC is the total fuel cost ($/h), and the Coefficients of fuel price of i^{th}generator unit that reflect the valve-point effect are$e_i$andf_i.

I.2.5 Limits on Ramp Rates

The generators are not capable to increase or decrease the output power instantly. Limitations on ramping up and down can be expressed as:

$$P_i - P_i^0 \leq UR_i \tag{I.7}$$

$$P_i^0 - P_i \leq DR_i \tag{I.8}$$

Where $P_i^0$the previous operating is output power of i^{th} unit (MW); DR_i and $UR_i$are thedown-rate and up-rate limits of i^{th} unit (MW/h), respectively. By considering both ramprate restrictions and limits on actual power output the equation is:

$$[max(P_i^{min}, P_i^0 - DR_i)] \leq P_i \leq min[P_i^{max}, (P_i^0 + UR_i)] \tag{I.9}$$

I.2.6 Prohibited operating zones

Due to machine component constraints or worries about instability, a limited operation zone may exist for producing units. The generator's possible operating zones as Shawn in (I.10)**[7]**:

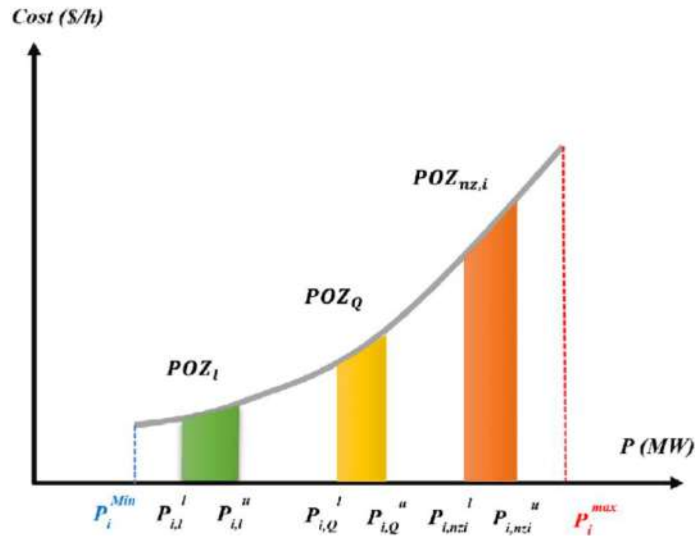

Figure I.1: Fuel cost function curve with prohibited operating zone.

$$\begin{cases} P_i^{min} \le P_i \le P_{i,1}^{lower} \le \\ P_{I,j-1}^{upper} \le P_i \le P_{i,j}^{lower} \; j = 2,3, \dots PZ_i \, ; \forall \; i\epsilon n \\ P_{i,PZ_i}^{upper} \le P_i \le P_i^{max} \end{cases} \tag{I.10}$$

Where j represents the number of prohibited operatingzones of unit i. $P_{i,j}^{lower}$ lower limit of jth prohibitedoperating zone and $P_{i,j-1}^{upper}$is the upper limit of$(j-1)^{th}$prohibited operating zone of i^{th}unit. PZ_i is the total number ofPOZ of i^{th} unit.

It is noted that unit i with PZ_i prohibited zones will have $PZ_i + 1$disjoint operating regions. These disjoint regions form anon-convex set.

I.2.7 Emission constrained dispatch (ECD)

Total emissions released by thermal power plants also can be approximated as a quadratic function of the output active power of the units. The emission constrained dispatch (ECD) problem can be expressed as an optimization task to minimize the total amount of emissions, which is defined by (I.11):

$$E_T = \sum_i^n [10^{-2}(\alpha_i P_i^2 + \beta_i P_i + \gamma_i) + \mu_i \exp(\zeta_i p_i)] \tag{I.11}$$

Where $E_T$denotes the system's total emission in tones per hour.α_i, β_i, γ_i, μ_i, and$\zeta_i$are the coefficients of the emission corresponding of generator i.

I. 3 Multi-Objective Optimization

In the real world, any multi-objective optimization problem consists of several objective functions that need to be optimized simultaneously, along with certain equality constraints and inequality constraints. This MOOP can be formulated mathematically as : which is defined by (I.12):

$$\min F(x) = f_1(x), f_2(x), \cdots ,\ f_i(x) \quad i = 1, 2, \cdots, N \tag{I.12}$$

$$s.t.\, g_j(x) = 0, h_k(x) \leq 0 j = 1, 2, \cdots, J;\ K = 1, 2, \cdots, K;$$

Wheref_i, h_k and $g_j$are i^{th} objective function, k^{th} inequality constraint,and jth equalityconstraint respectively, x represents a decisionvector, and N, K, and J are respectively the number of multipleobjectives, inequality constraints, and equality constraints.

Any MOOP solution is not just one solution, as in the case of single objective OPF; it also gives a set of solutions called the tradeoff. The decision maker has to select one best solution from the Pareto set, known as the compromise solution. All the solutions in the trade-off obtained for MO algorithms utilize the principle of dominance. Let x_1 and x_2 be two solutions of MOOP. Then asolution x_1 is said to dominate x_2 if it satisfies the following twoconditions:

1. The solution x_1 is not worse than x_2 for all objectives, i.e. which is defined by (I.13):

$$\forall\ i \epsilon \{1, 2, \cdots, N\}: f_i(x_1) \leq f_i(x_2) \tag{I.13}$$

The solution x_1 is firmly better than x_2 for at least one objectivei.e. which is defined by (I.14):

$$\exists j \epsilon \{1, 2, \cdots, N\}: f_j(x_1) < f_j(x_2) \tag{I.14}$$

The solutions that are Non-Dominated within the entire search space are denoted as Pareto-optimal solutions.

The multi-objective optimization algorithm applied in this thesis utilize the concept of Non-

Dominated sorting and crowding distance techniques to find and manage the Pareto-optimal set. The detailed procedure for these two techniques is presented in**[2]**.

I. 3. 1 Best compromise solution

After having the Pareto-optimal set, a fuzzy-based mechanism is applied to extract the best compromise solution. Due to the imprecise nature of the decision maker's judgment, the ith objective function of a solution in the Pareto-optimal set Fi is represented by amembership function μi defined as **[8]**. which is defined by (I.15):

$$\mu_i = \begin{cases} 1 & f_i \leq f_i^{max} \\ \frac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} < f_i < f_i^{max} \\ 0 & f_i \geq f_i^{max} \end{cases} \qquad (I.15)$$

Where$f_i^{max}$and $f_i^{max}$are the maximum and minimum values of the$i$th objective function, respectively.

For each Non-Dominated solution$k$, the normalized membershipfunction $\mu_k$is calculated as

$$\mu_k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{j=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^j}$$

Where M is the number of Non-Dominated solutions? The best compromisesolution is the onehaving the maximum ofμ_k. As a matter offact, arranging all solutions in the Pareto-optimal set in descendingorder according to their membership function will provide the decision maker with a priority list of Non-Dominated solutions. This will guide the decision maker in view of the current operating conditions.

I.4. Conclusion

In conclusion, combined economic and emission dispatch (CEED) is a significant optimization problem in power system operation that aims to minimize both the cost of generation and the emissions of pollutants simultaneously. It involves determining the optimal generation output for each power generator in a system, considering the economic factors such as fuel costs and the environmental factors such as emissions limits.

The CEED problem is challenging because there is a trade-off between minimizing costs and reducing emissions. Power systems need to meet the demand for electricity at the lowest possible cost, but at the same time, there is an increasing concern about environmental sustainability and the need to reduce greenhouse gas emissions.

The second chapter study the multi-objective imperialist completive algorithm (MOICA).

Chapter II:Multi-Objective Imperialist Competitive Algorithm MOICA

II.1.Introduction

In this chapter, the application of multi-objective imperialist competitive algorithm is investigated for solving economic and emission dispatch problem. It is aimed to minimize two conflicting objectives, economic and environmental, while satisfying the problem constraints. In addition, nonlinear characteristics of generators such as prohibited zone and ramp up/down limits are considered. To check applicability of the MOICA, it is applied to 12 h of IEEE 30-bus test system. Then, results of MOICA are compared with those derived by non-dominated sorting genetic algorithm and multi-objective particle swarm optimizer. The finding indicates that MOICA exhibits better performance.

The Multi-Objective Imperialist Competitive Algorithm (MOICA) is a metaheuristic optimization algorithm inspired by the concept of imperialism and competition among nations. It is designed to solve multi-objective optimization problems, which involve optimizing multiple conflicting objectives simultaneously.

The MOICA algorithm follows a population-based approach, where a set of candidate solutions, known as imperialists, compete with each other for dominance in a given search space. Each imperialist represents a potential solution to the problem, and the quality of the imperialist is determined by its fitness value, which is evaluated based on the objectives being optimized.

In MOICA, the population is divided into two groups: imperialists and colonies. The imperialists are the elite individuals that represent the best solutions found so far, while the colonies are the remaining candidate solutions. The colonies are associated with an imperialist, and they collaborate with their respective imperialist to improve their fitness and overall performance.

The algorithm operates in several iterations, called epochs. In each epoch, the imperialists expand their influence by assimilating nearby colonies. The colonies undergo transformations to improve their fitness and move closer to their associated imperialist. The algorithm also incorporates a mechanism to balance exploration and exploitation to ensure a good balance between exploring the search space and exploiting promising regions.

The MOICA algorithm utilizes a dominance-based ranking approach, such as the Pareto dominance, to compare and select solutions based on their fitness values. It aims to find a set of solutions that are not dominated by any other solutions, known as the Pareto front. These solutions represent the trade-off between the conflicting objectives and provide a range of optimal solutions for decision-makers to choose from.

II. 2.Multiobjective imperialist competitive algorithm

A. Imperialist Competitive Algorithm

Imperialism is the policy of extending the power and rule of a government beyond its own boundaries. A country may attempt to dominate others by direct rule or by less obvious means such as a control of markets for goods or raw materials. The latter is often called neocolonialism **[9]**. ICA is a novel global search heuristic that uses imperialism and imperialistic competition process as a source of inspiration. This algorithm starts

With some initial countries. Some of the best countries are selected to be the imperialist states and all the other countries form the colonies of these imperialists. The colonies are divided among the mentioned imperialists based on their power. After dividing all colonies among imperialists and creating the initial empires, these colonies start moving toward their relevant imperialist state. This movement is a simple model of assimilation policy that was pursued by some imperialist states **[10]**. Figure 1 shows the initial empires. Accordingly, bigger empires have greater number of colonies where weaker ones have less. In this figure, Imperialist 1 has formed the most powerful empire and consequently has the greatest number of colonies.

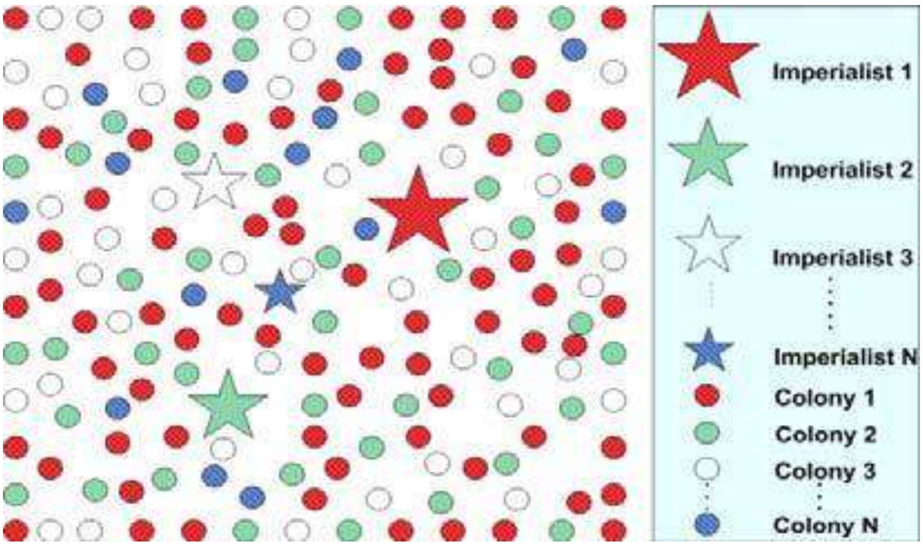

Figure II.1. Generation of initial empires

B. Movement of Colonies toward the Imperialist

It is clear that, imperialist countries start to improve their colonies. We have modeled this fact by moving all the colonies toward the imperialist. Figure 2 shows a colony moving toward the imperialist by units. The direction of the movement is shown by the arrow extending from a colony to an imperialist **[11]**. In this figure *x* is a random variable with uniform (or any proper) distribution. Then for *x* we have: which is defined by (II.16):

$$x \approx \times U\, d\, (0,)\, \beta \qquad \text{(II.16)}$$

where *d* is the distance between the colony and the imperialist state. The condition $\beta > 1$ causes the colonies to get closer to the imperialist state from both sides.

After dividing all colonies among imperialists and creating the initial empires, these colonies start moving toward their relevant imperialist state which is based on assimilation policy **[12]**. Figure 3 shows the movement of a colony towards the imperialist. In this movement, θ and x are random numbers with uniform distribution as illustrated in Equation (2) and d is the distance between colony and the imperialist. which is defined by (II.17):

$$x\, U\, d\, U \approx \times \approx - (0,), (,)\, \beta\, \theta\, \gamma\, \gamma \qquad \text{(II.17)}$$

Where β and γ are parameters that modify the area that colonies randomly search around the imperialist.

The total power of an empire depends on both the power of the imperialist country and the power of its colonies. In this algorithm, this fact is modeled by defining the total power of an empire by the power of imperialist state plus a percentage of the mean power of its colonies. Any empire that is not able to succeed in imperialist competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated

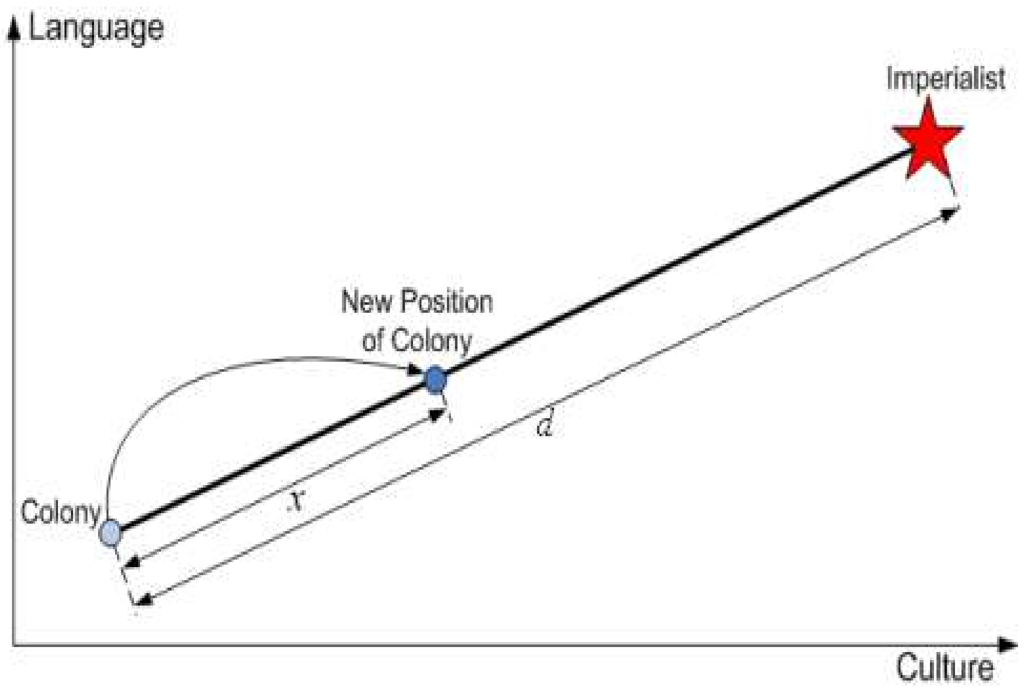

Figure II.2. Movement of colonies toward their relevant imperialist

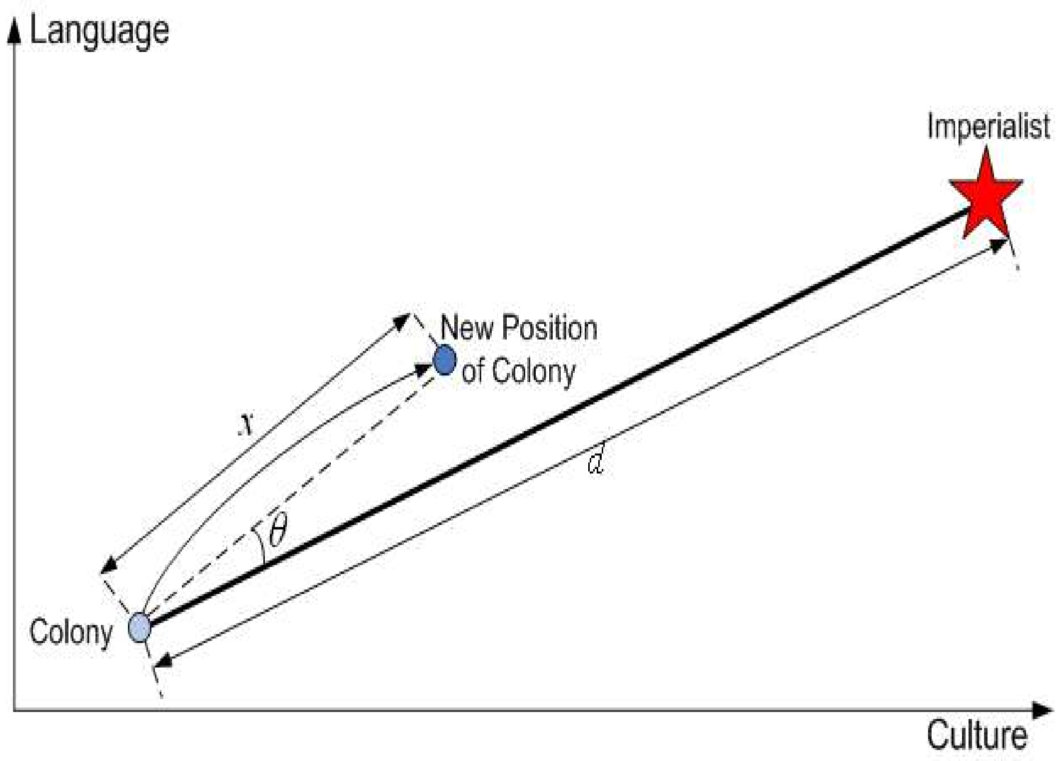

Figure II.3. Movement of colonies toward their relevant imperialist in a randomly deviated direction

The imperialistic competition will gradually result in an increase in the power of great empires and a decrease in the power of weaker ones. Weak empires will lose their power gradually and ultimately they will collapse **[13]**. The movement of colonies toward their relevant imperialists along with competition among empires and also collapse mechanism will hopefully cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are its colonies. In this ideal new world colonies have the same position and power as the imperialist. Figure 4 shows a big picture of the modeled imperialistic competition. Based on their total power, in this competition, each of the empires will have a likelihood of taking possession of the mentioned colonies.

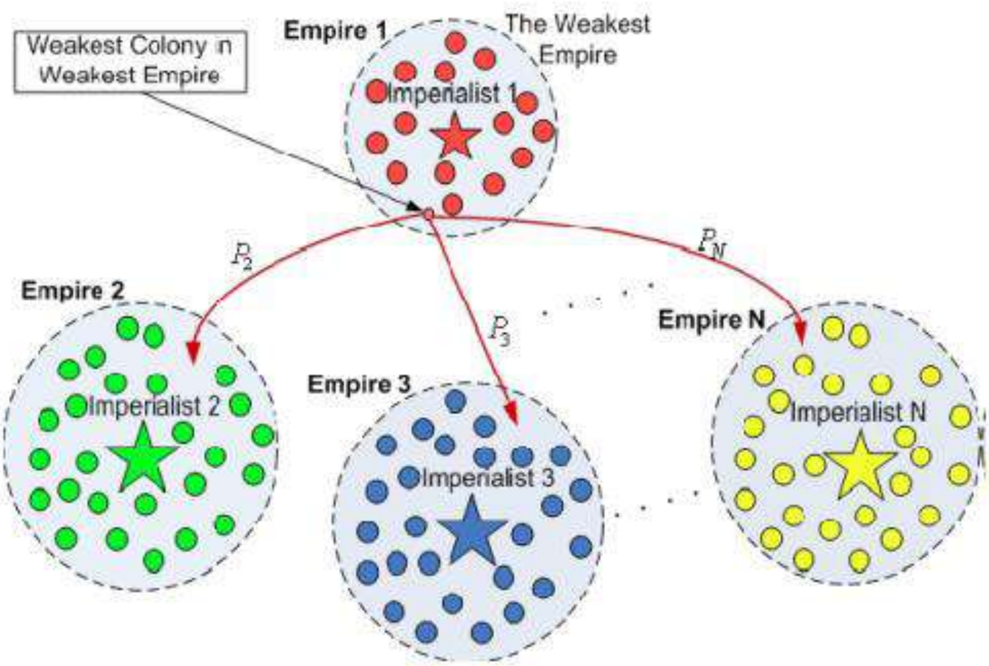

Figure II.4. Imperialistic competition: The more powerful an empire is the more likely it will possess the weakest colony of weakest empire

Phase one:	***Phase two:***

for each p·P
for each q·P
if(p≺q) then
S_p=S_p U {q}
else if (q≺p)then
n_p=n_p+1
if n_p = 0 then
F_1 =F_1 U {p}
	i=1
	While F_i· Ø
	H · Ø
	For each p · F_i
	For each q · S_p
	n_q=n_q-1
	if n_q = 0 then H = H U {p}
	I = i+1
	F_i = H

Table II.1. **T**he pseudcode of ICA

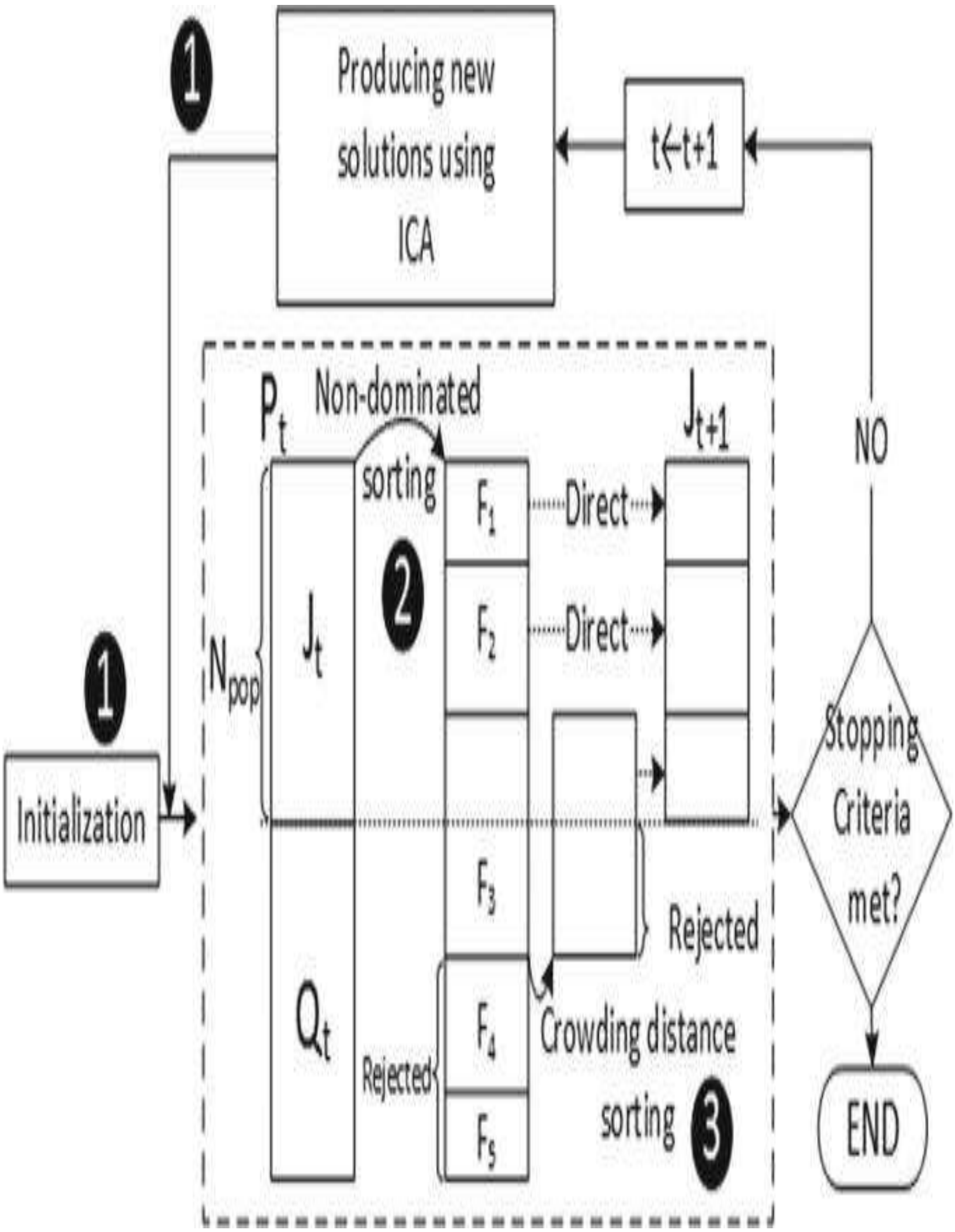

Figure II.5. The whole process of MOICA

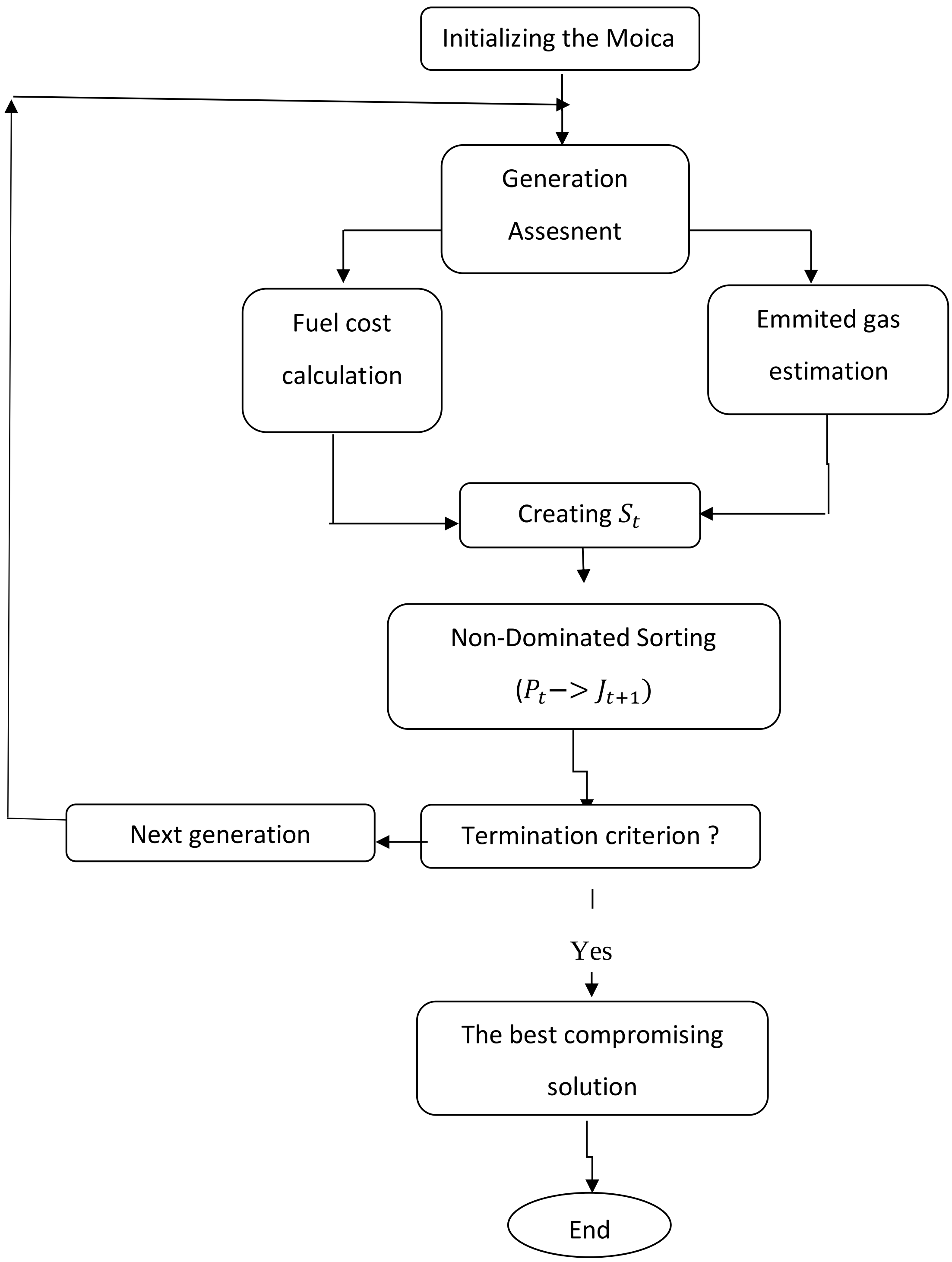

Figure II.6. Process of using MOICA for solving EED problem.

II.3.Conclusion:

This paper has studied the application of multi-objective imperialist completive algorithm (MOICA) to solve emission and economic dispatch (EED) problems. In this regard, the algorithm has been applied for solving EED problem of a IEEE 30-bus test system. the non-linear characteristics of generators such as valve-point loading and prohibited zone along with other constraints of the system are considered. For comparison purpose, the results of MOICA are compared with results of NSGA-II and MOPSO, which indicate better performance of MOICA.

Chapter III: Simulation and results

Chapter III Simulation and results

III.1.Introduction

The EED optimization problem formulated as multi-objective optimization problem with competing objectives of fuel cost, emission and system loss. This difficult optimization problem is solved by using the MOICA algorithm. ICA is a global search strategy that uses the socio-political competition among empires as a source of inspiration. Similar other evolutionary ones that start with initial population, this technique begin by initial empires. During the competition, weak empires collapse and powerful ones take possession of their colonies which improve the algorithm. The achieved numerical results of the proposed technique demonstrate the feasibility of the proposed technique to solve the multi-objective EED problem

This formulation was done using the existing quadratic functions that define fuel cost functions and emission along with valve point loading effects which were responsible for discontinuities in the cost curves as well its non-convex nature. With the use of the weighting functions which were varied from 1 to 2 for both

An IEEE test system with 6 generators IEEE test system with 3generators

Opposition-based positioning enhances the performance of the algorithm, the sample problem has been solved

III.2.Computer program

The proposed MOICA algorithm has been developed and implemented using the MATLAB 2017 on a personal computer (Intel(R) Core(TM) i3-3110M processor, 500 GB, 2.40GHz speed)

Multi-objective Economic and Emission Dispatch

III.3.formulation

We utilized both IEEE network models, including three generators and six generators, to conduct our studies. For the three-generator setup, we focused on solving the static combined economic emission dispatch problem for a power system consisting of three units. In this case, our objective was to optimize the economic and emission aspects simultaneously.

On the other hand, in the case of the six-generator setup, we dealt with the dynamic combined economic/environmental dispatching (CEED) problem. This dynamic optimization problem aimed to optimize the trade-off between economic considerations and environmental factors in real-time operation. By considering both economic and environmental aspects, we aimed to find optimal dispatch strategies for the six generators within the power system.

These studies allowed us to explore and address different aspects of power system optimization, considering both the static and dynamic dispatch scenarios. By optimizing the economic and environmental factors simultaneously, we aimed to find efficient and sustainable solutions for power system operation and management.

Problem proposition

III.4.1.Test system 1: three unit system

In this particular test system, there are three generating units or power plants. Each unit is characterized by its own operating cost curve, which represents the relationship between the power output of the unit and its corresponding operating cost. The operating costs typically include fuel costs, maintenance costs, and other operational expenses.

The goal of the multi-objective optimization problem in this test system is to determine the optimal power generation schedule for the three units that minimizes both the total generation cost and the emissions produced by the system. The emission constraints are usually set based on environmental regulations or desired emission reduction targets.

Powre demand	1	2	3	4
Load demand (MW)	200	250	300	400

Table III.1. Load demand for 4 hours

unit	P_{min}**(MW)**	P_{max}**(MW)**
1	35	210
2	130	325
3	125	315

Table III.2. Upper and lower limits three unit

unit	a[$ / MW^2 h]	b[$ / MW h]	c[$ / h]
1	0.03546	38.30553	1243.5311
2	0.02111	36.32782	1658.5696
3	0.01799	38.27041	1356.6592

Table III.3. data cost

unit	A	β	γ	ζ	ʎ
1	0.00683	-0.54551	40.2669	0	0
2	0.00461	-0.5116	42.89553	0	0
3	0.00461	-0.5116	42.89553	0	0

Table III.4. data emission

<u>The B- coefficients three unit system</u>

```
B1=0.0001.*[0.710  0.30   0.25
            0.300  0.69    0.32
            0.255  0.32   0.80]
B=B1(1:3,1:3);
B0=[0 0 0];
B00=0;
```

Power demand	**Pd(MW)**	**P1(MW)**	**P2(MW)**	**P3(MW)**	**Emission**	**Fuel cost**	**Loss(MW)**
1	200	87.7064	168.7203	150.8068	203.3569	20801.9221	7.2335
2	250	88.2919	168.0551	150.8819	203.1149	20802.3930	7.2289
3	300	91.1767	165.0664	150.9641	202.0889	20805.2540	7.2072
4	400	103.6367	153.3799	150.1105	199.9453	20828.2157	7.1271

Table III.5. Simulation results of MOICA fuel cost end fuel emission

The above table represents the results obtained according to the combined initial characteristics.

We notice that P1(MW) increases in terms of power demand , P2(MW) decreases, P3(MW) increases

We observe an inverse proportion of emission , fuel cost .and decreases power losse

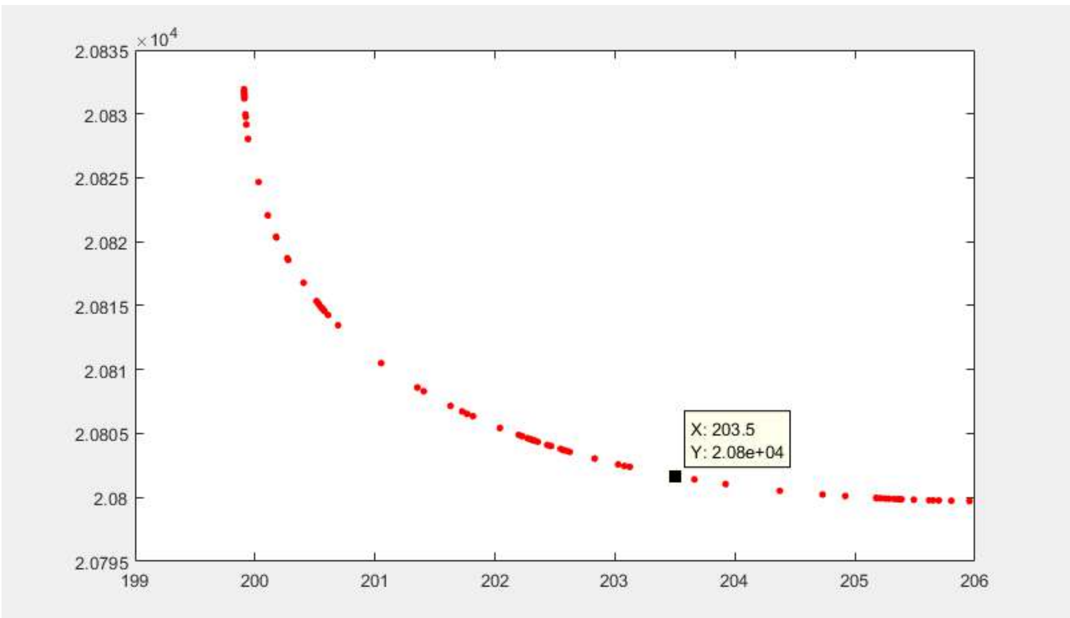

Fig III.1. Three units plot of configuration results

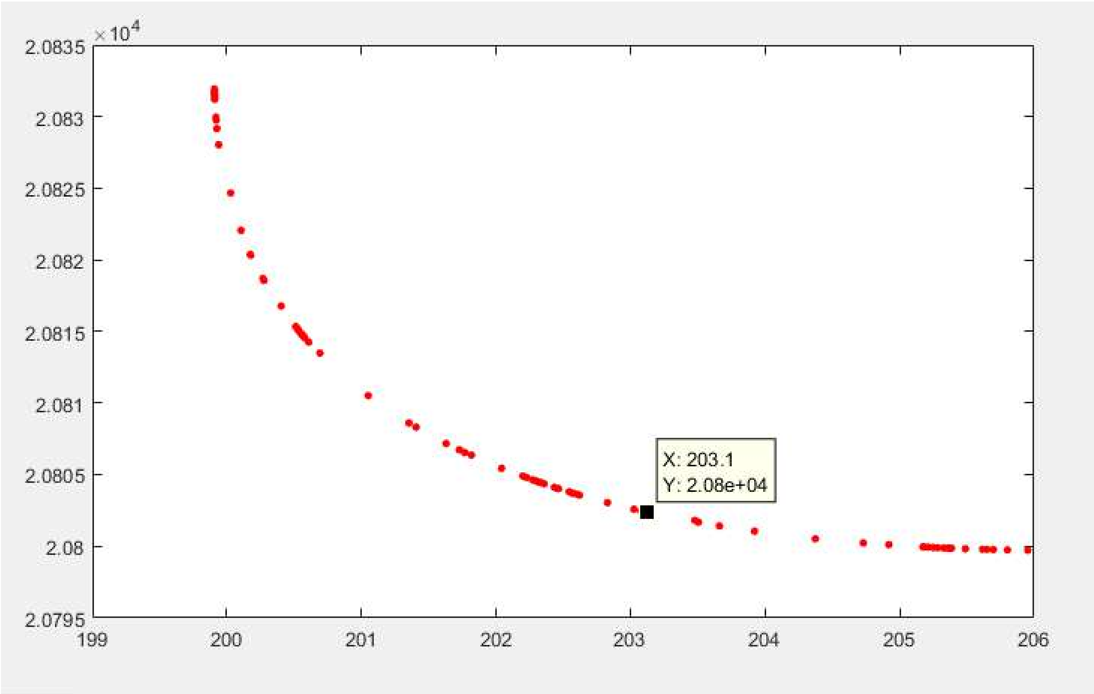

Fig III.2. Three units plot of configuration results

Curve **III** (**1.2**) represents fuel cost ,emission and it is in the form of an inverted function and the goal is to find the optimal point whose coordinates are (x,y),((203.1,2.08e+4)

unit	a[$ / MW^2 h]	b[$ / MW h]	c[$ / h]
1	0.0070	7.0	240
2	0.0095	10.0	200
3	0.0090	8.5	220
4	0.0090	11.0	200
5	0.0080	10.5	220
6	0.0075	12.0	190

Table III.6. data cost six unit

II.4.2.Test system 2: Six unit system

In order to test the effectiveness of the proposed method, initially a small test system consisting of six generating units is considered.

The practical constraints of ELD problems such as prohibited operating zones and ramp-rate limits are considered to verify the efficacy of the proposed method under practical environment.

Unit	A	β	γ	Xi	Delta
1	4.091	-5.554	6.490	0.000200	2.857
2	2.543	-6.047	5.638	0.000500	3.333
3	4.258	-5.094	4.586	0.000001	8.000
4	5.426	-3.550	3.380	0.002000	2.000
5	4.258	-5.094	4.586	0.000001	8.000
6	6.131	-5.555	5.151	0.000010	6.667

Table III.7. Data emission six unit

Unit	P_{min}(mw)	P_{max}(mw)
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
6	50	120

Table III.8. Upper and lower limits six unit

Unit	P now(MW)	UR(MW h)	DR(MW h)
1	440	80	120
2	170	50	90
3	200	65	100
4	150	50	90
5	190	50	90
6	110	50	90

Table III.9.down rate and up rate limits six unit

<u>The B- coefficients six unit system</u>

B_c=[0.0017,0.0012,0.0007,-0.0001,-0.0005,-0.0002;

0.0012,0.0014,0.0009,0.0001,-0.0006,-0.0001;

0.0007,0.0009,0.0031,0.0000,-0.0010,-0.0006;

-0.0001,0.0001,0.0000,0.0024,-0.0006,-0.0008;

-0.0005,-0.0006,-0.0010,-0.0006,0.0129,-0.0002;

-0.0002,-0.0001,-0.0006,-0.0008,-0.0002,0.0150]

HOUR	Pd	P1	P2	P3	P4	P5	P6	Fuel cost[$ / h]	Emission [$ / h]	Loss(MW)
1	955	285.9912	104.3908	106.5789	95.4907	103.2048	82.2984	1358,9392	13,1659	11,6830
2	942	372.8262	178.1243	165.3505	131.3953	164.0639	127.5718	1355,7972	12,9911	11,8305
3	935	349.7585	231.2778	249.6190	125.6325	130.2569	111.2957	1352.7964	13.1195	11.5406
4	930	323.1136	133.8175	205.6453	91.6574	102.0109	81.2180	1356.7026	12.9634	11.5436
5	935	320.3325	125.6918	214.7648	95.3299	101.3150	89.3105	1352.4998	13.0736	12.0943
6	963	320.1424	127.1910	235.1229	102.2153	118.1402	91.6628	1340.2632	14.2559	12.2797
7	989	313.6442	136.6597	225.4524	114.9488	115.2928	94.6788	1352,4495	13,9098	12,0010
8	1023	320.1177	138.2733	234.4477	103.0355	130.7642	98.3116	1336,0858	15,5420	12,9391
9	1126	379.3279	82.3373	105.5397	102.4166	105.6482	95.6870	1349,1991	16,1383	13,2292
10	1150	320.3611	95.0647	118.2418	90.6294	124.8507	81.7770	1335,8644	17,7213	14,2059
11	1201	385.5065	188.5158	274.4793	139.8820	182.9677	114.1930	1339,4107	17,0508	14,7008
12	1235	414.3182	180.7303	207.7628	138.7969	190.3211	116.5480	1336.4596	18.6108	15.1055

Table III.10. the result of compromising solution in each hour 6unit

The above table represents the results obtained according to the combined initial characteristics.

We notice fuel cost increases and emission decreases, an inverse proportion between fuel cost and emission

We note that the fuel cost is directly proportional to loss and inversely proportional to emission

We note that the fuel cost is directly proportional to loss and inversely proportional to emission

H	Fuel cost[$ / h]	Emission[$ / h]	loss(MW)
1	1339.1059	14.7498	11.9265
2	1350.0818	14.0059	11.3307
3	1352.7964	13.1195	11.5406
4	1356.7026	12.9634	11.5436
5	1352.4998	13.0736	12.0943
6	1340.2632	14.2559	12.2797
7	1352,4495	13,9098	12,0010
8	1336,0858	15,5420	12,9391
9	1349,1991	16,1383	13,2292
10	1335,8644	17,7213	14,2059
11	1339,4107	17,0508	14,7008
12	1336.4596	18.6108	15.1055

Table III.11.the result of compromising solution in each hour 6unit

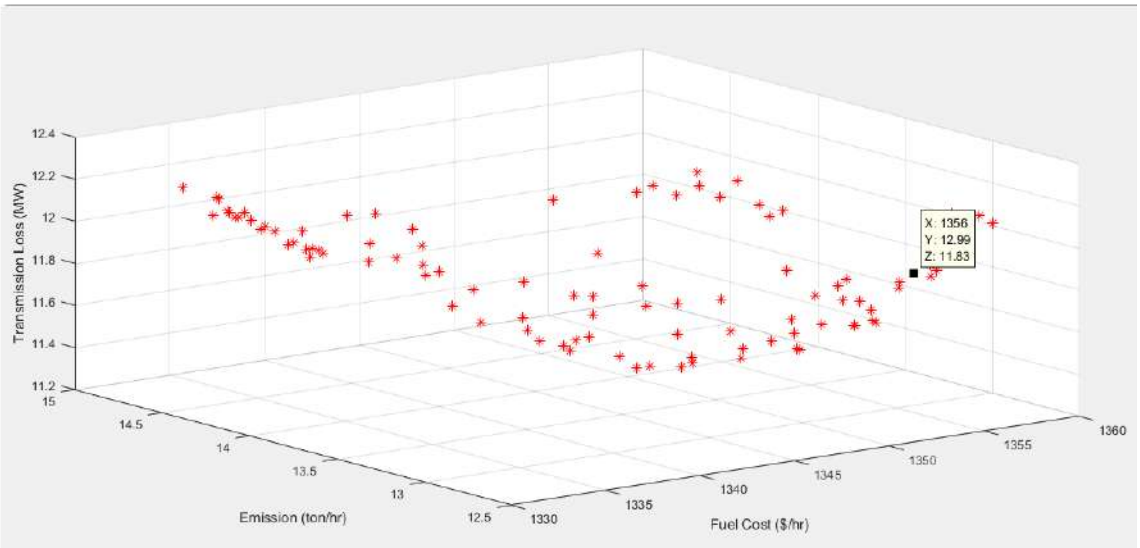

Fig III.3. Six units plot of configuration results

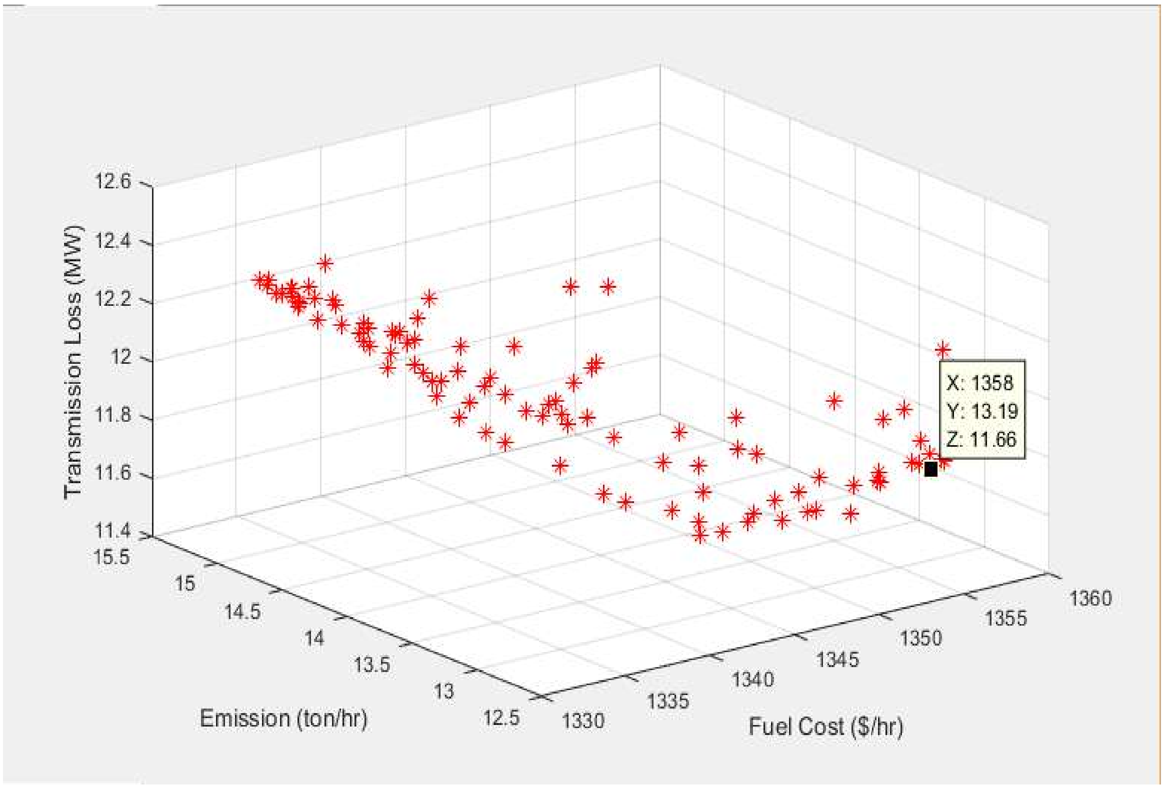

Fig III.4. Six units plot of configuration results

The third curve III (3.4) represents fuel cost in terms of emissions end loss In a system of six units, the aim of which is to find the optimal point and its coordinates (x,y,z),(1358,,13.19,11.66)

III.5.Initialization of Algorithm

To initialize the MOICA, random values are chosen by considering maximum/minimum capacity of units, ramp rating limits and prohibited zones. This process increases accuracy of algorithm while reduces number of fitness function evaluations. Same method is applied to produce new generation of solutions in each iteration. Shows the feasible values for a given thermal units by considering the constrains (dark green areas).

III.6.Conclusion

The simulations and results obtained from the application of optimization algorithms to solve the Combined Economic Emission Dispatch (CEED) problem have demonstrated their competence in achieving optimal solutions that balance economic efficiency and environmental sustainability. These algorithms provide valuable decision support for power system operators and planners, enabling them to optimize power generation schedules while considering both cost minimization and emission reduction objectives.

By incorporating accurate and up-to-date data, the optimization algorithms can effectively handle the complexity of the CEED problem and explore the trade-offs between economic and environmental factors. The simulations have shown that various optimization techniques, such as linear programming, quadratic programming, genetic algorithms, and particle swarm optimization, among others, can be employed to find solutions that meet operational constraints while minimizing generation costs and reducing emissions.

The results obtained from these simulations provide insights into the optimal allocation of generation resources, considering factors such as fuel costs, power plant efficiencies, emission factors, and system constraints. They highlight the importance of balancing economic and environmental objectives and provide decision-makers with a range of optimal solutions to choose from based on their priorities and preferences. Regular data updating and monitoring are crucial to ensuring the accuracy and reliability of the optimization process.

Overall, the application of optimization algorithms to the CEED problem represents a promising approach to achieve more sustainable and efficient power systems. By integrating economic and environmental considerations, these algorithms contribute to the development of greener energy solutions while optimizing the utilization of available resources. Continued research and advancements in optimization techniques will further enhance their effectiveness in addressing the challenges of combined economic emission dispatch in power systems

General Conclusion

General Conclusion

In conclusion, multi-objective optimization algorithms provide effective solutions for solving the Combined Economic Emission Dispatch (CEED) problem. CEED involves the simultaneous consideration of economic costs and emissions reduction in power systems.

The application of multi-objective optimization algorithms in CEED facilitates the determination of optimal generation schedules for power plants. It considers factors such as emission constraints, operational costs, power limits, and environmental regulations. This enables decision-makers to make informed choices that strike a balance between economic efficiency and environmental sustainability.

Furthermore, multi-objective optimization algorithms provide decision-makers with a range of optimal solutions. This flexibility allows them to select the most appropriate solution based on their specific requirements, preferences, and policy frameworks. By optimizing the combined economic distribution of emissions, these algorithms contribute to the development of cleaner and more sustainable energy systems.

In summary, multi-objective optimization algorithms offer powerful tools for addressing the CEED problem. They enable decision-makers to achieve more efficient and environmentally friendly power system operations, leading to reduced environmental impact and improved economic performance in the generation and distribution of power. By integrating these algorithms into decision-making processes, organizations can work towards achieving a harmonious balance between economic objectives and emission reduction goals.

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