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Solution of the Multi-objective Economic and Emission Load Dispatch Problem Using Adaptive Real Quantum Inspired Evolutionary Algorithm

Jitender Singh[1], Ashish Mani[2], H.P. Singh[3], Dinesh Singh Rana[4]
[1]Ph.D. Scholar, EEE Department Amity University,
Noida,Uttar pradesh, India.
jitender.singh3@student.amity.edu
https://orcid.org/0000-0002-7330-6997
[2]Professor, EEE Department, Amity University,
Noida,Uttar pradesh, India.
amani@amity.edu
https://orcid.org/0000-0002-2312-1185
[3]Professor, EEE Department, Amity University,
Noida,Uttar pradesh, India.
hpsingh2@amity.edu
https://orcid.org/0000-0001-9207-2703
[4]Professor, Department of Instrumentation, U.S.I.C., Kurukshetra University,
Kurukshetra, Haryana, India
rana.kuk@gmail.com
https://orcid.org/0000-0003-4157-2059

Abstract— Economic load dispatch is a complex and significant problem in power generation. The inclusion of emission with economic operation makes it a Multi-objective economic emission load dispatch (MOEELD) problem. So it is a tough task to resolve a constrained MOEELD problem with antagonistic multiple objectives of emission and cost. Evolutionary Algorithms (EA) have been widely used for solving such complex multi-objective problems. However, the performance of EAs on such problems is dependent on the choice of the operators and their parameters, which becomes a complex issue to solve in itself. The present work is carried out to solve a Multi-objective economic emission load dispatch problem using a Multi-objective adaptive real coded quantum-inspired evolutionary algorithm (MO-ARQIEA) with gratifying all the constraints of unit and system. A repair-based constraint handling and adaptive quantum crossover operator (ACO) are used to satisfy the constraints and preserve the diversity of the suggested approach. The suggested approach is evaluated on the IEEE 30-Bus system consisting of six generating units. These results obtained for different test cases are compared with other reputed and well-known techniques.

Keywords- power system; meta-heuristics; multi-objective; economic load dispatch, Quantum inspired Evolutionary Algorithms;

Nomenclature			
f_{cost}	Fuel cost function	$f_{emission}$	Emission function
$C_j(PG_j)$	Fuel cost of jth unit	$E_j(PG_j)$	Emission from jth units
x_j, y_j, z_j	Fuel cost coefficients	$a_j, b_j, c_j, \zeta_j\ \lambda_j$	Emission coefficients
N	Number of generating units	P_{demand}	Power demand of consumers
$PG_j^{\min}, PG_j^{\max}$	Minimum and maximum power generation limits	P_{loss}	Transmission Power losses
PG_j	Power generation of jth unit	B_{1j}, B_{0j}, B_{00}	Coefficient of power losses

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I. INTRODUCTION

The raise in the electric power demand every year leads to a focus on the profitable use of energy resources. The efficient use of energy sources and proper scheduling of the power-generating units are important aspects to generate power at a lower cost. Economic Load Dispatch is an important process in electrical power generation. The prime objective of this process is to minimize the cost. The present work is focused on the Economic load dispatch problem. Economic load dispatch (ELD) is a complex, non-aligned constrained optimization process of power generation level allotment to the power generating unit at the lowest possible cost of generation. The prime target of the ELD is to decrease the fuel cost of power production by gratifying all the constraints of the power generating units. The prime constraints are load balance constraint, and maximum and minimum power generation bounds [1]. A particle swarm optimization (PSO) technique is used to deal with an economic load dispatch problem (ELDP) [2] with two different unit tests (3 units and 6 units) systems. All the constraints are gratified in this work. An optimal ELD has a great impact on the stability, quality, and safety of the system. So, it becomes an important and complex task to solve ELDP to overcome these issues. A Jaya algorithm is used to solve the ELDP [3] to enhance the system stability, and safety. The valve point impact is also considered to reduce the cost of power generation. A Tasmanian devil optimization algorithm (TDOA) inspirited by the food search method of the Tasmanian devil is used to carry out the ELDP [4]. The prime focus of the suggested approach is on optimal dispatch and cost reduction while ignoring other issues. The results of the suggested approach are found quite effective. ELD has a significant role in emission reduction, lowering fuel costs, and conservation of energy. A fitness-dependent optimizer (FDO) approach along with the weight factor is used to solve the ELDP [5] to meet the fittest possible result to the problem. The suggested work carried out is to reduce emissions, losses, and cost reduction. A 24-unit test case is used to test the proposed approach of the FDO. Similar work to [3] is also carried out in [6] considering the effect of valve point loading to solve ELDP with constraint satisfaction. The ELDP is solved using the hybrid approach of the gravitational Search algorithm (GSA) and hill climbing algorithm (HCA). The current hybrid algorithm was tested on a 15-unit system. A teaching and learning-based optimization algorithm (TLBOA) is used to resolve an ELDP [7]. The TLBOA was tested on a six-unit test case with constraint satisfaction.

A hybrid algorithm of the simplex search method (SSM) and artificial algae algorithm (AAA) is for the solution of an ELDP [8] addressed as a hybrid artificial algae algorithm (HAAA). The AAA algorithm is inspired by the life cycle of algae [8]. A similar approach to [3,6] is used in [9] considering the multiple fuels and loading effect of valve point to carry out an ELD problem using a crow search algorithm (CSA). The results of the suggested approach are found satisfactory. A grid service-based model of ELDP is suggested in [10] for the multi-area system. The suggested model is designed wonderfully so that each node is capable to provide a feasible solution for EDP. The utilization of a reliability indicator to settle an ELD problem with enhanced reliability is suggested in [11]. The exchange market algorithm (EMA) is used to search for the optimal ELD solution. A test case of 26 units is used for testing the efficiency of the algorithm to enhance reliability and reduce the cost of operation.

Most of the ELDPs have a prime objective to reduce fuel costs and are solved as a solo-objective problem. The interest of the researcher is increasing to carry out a manifold objectives ELD problem. The most common second objective included in ELDP is the Emission reduction approach to solve the BI-Objective/Multi-objective Economic Emission Load Dispatch Problem (BOEELDP/ MOEELDP). There are other objectives like turbine valve point loading, reliability, stability, etc also considered in different works suggested further. A differential evolution algorithm is utilized for the solution of the multi-objective EELDP (MOEELDP) to minimize the emission and the cost of fuel consumption [12]. The suggested approach is verified on the IEEE 30-bus test case system and (6 units and 40 units) test case systems. The suggested approach can lower the emission and cost of generation. A non-dominated sorting differential evolution algorithm (NS-DEA) is applied to solve the MOEELD problem [13]. The suggested NSDEA is capable to provide satisfactory and improved results. A bacterial colony chemo-taxis algorithm (BCCA) is used to solve a MOEELDP in [14] considering the reduction of CO_2, SO_2, and NO_2. The suggested BCCA can achieve the environmental objective with a low cost of fuel for power generation at fast convergence. A hybrid approach of steady-state genetic algorithm (SSGA) and ant colony optimization algorithm (ACOA) is used to figure out the solution for an economic emission load dispatch (EELD) problem [15]. The suggested technique attains robust nature and solves the EELD problem in a constrained environment. An approach of non-dominated sorting genetic algorithm II (NDSGA-II) is applied to carry out the MOEELD problem [16] considering the emission index. The NSGA-II is also used to deal with a MOEELD in [17] considering adaptive crowding distance. The results are found very impressive in comparison to other algorithms. A multi-objective bacterial foraging (MOBF) algorithm is used to solve a MOEELD problem [18]. The proposed MOBFA used the IEEE 30-bus system consisting of six generators to evaluate the efficiency of the current method. The findings prove the capability of the suggested technique. A hybrid method consisting of a local search (LS) and a Genetic algorithm (GA) is used to find the solution to a MOEELD problem [19]. The current work also adopts a repair-based

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constraint handling technique and this technique is applied to repair the constraints. The present algorithm is evaluated on the IEEE 30-bus system consisting of six generating units and the outcomes support the capability of the algorithm. A combined approach of modified population variant differential evolution algorithm (MPVDEA) and modified NSGA-II (MNSGA-II) is applied to solve a MOEELD problem along a special operator to prevent \ convergence issue [20]. The suggested hybrid method was tested on various IEEE test systems to analyze the quality and efficiency of the algorithm. A moderate random search particle swarm optimization algorithm (MRPSO) was used to solve a MOEELD problem [21]. The testing of the suggested MRPSO was completed on IEEE 30 Bus system and the objective of emission and economic load dispatch with effective results are obtained. The particle swarm optimization (PSO) is also applied [22] to carry out the multi-area economic load dispatch (MAELD) problem.

A multi-objective PSO (MOPSO) is used to solve an EELDP in [23] along with a test case of the IEEE system (30 bus system). The suggested MOPSO is capable of providing enhanced load allocation in comparison to other techniques. An NSGA_II is applied to clarify the solution for an emission-based ELD problem [24]. The suggested technique was also verified on IEEE (30-bus) system. The outcomes obtained are found competitive with other known methods. The works suggested in [1-11] are based on a single-objective ELDP. The work suggested in [12-24] and [27-31] is focused on the emission-based Multi-objective economic emission load dispatch problem (MOEELDP). The ELDP may be formulated as a solo-objective, Bi-objective, or multi-objective problem depending upon the system's environment and researchers. The earlier discussed ELD problem has been solved in a constrained environment with various kinds of solution methods. A variety of solution methods and algorithms are suggested in various works during different periods. Some other works are also considered in the literature survey. The NSGA-II is applied in [27] to solve a MOELDP. Similarly, the MOEELDP problems are solved in [28-30] by the authors using different algorithms and test cases. Some of the test cases from this work are also adopted in the current work. A multi-objective EELDP is carried out in [31] using a multi-objective stochastic search algorithm (MOSST). All the work discussed in [1-31] suggests various types of solution techniques (classical methods, nature-inspired methods, and hybrid methods) to figure out the ELDP with single/multiple objectives.

Today the evolutionary algorithms are standing in the front row of solution methods/techniques to carry out a complex, optimization problem with different objectives in a constrained environment [25-26]. The evolutionary algorithms (EAs) are capable to find the fittest solution in the problem solving of ELD problems and other problems. The EAs have also some limitations like the issue of premature convergence, slow convergence issues, a requirement for efficient parameter tuning, etc. the performance of the EAs depends on different operator and input parameters used to settle the problem. EAs are not able to differentiate between the prime function and the various constraints of the system. So, EAs require a separate method to handle and satisfy the various constraints of the generating units and system. All issues discussed above are resolved by suggesting the enhanced variant of the Quantum-inspired evolutionary algorithm (QIEA).

The current work is carried out to investigate the effectiveness of the suggested MO-ARQIEA in solving the EELDP and evaluate various parameters concerned with the problem. The present work is carried out using a bi-objective Adaptive real coded Quantum inspired evolutionary algorithm (MO-ARQIEA). The EELDP is solved efficiently in the present work by overcoming all issues faced by EAs. The suggested algorithm is inspired by quantum mechanics principles and it is structured as an evolutionary algorithm [25]. The suggested MO-ARQIEA is structured as a non-dominated sorting approach in the EAs framework with the adoption of quantum principles and real coded variables to solve a bi-objective EELDP. The advantage of the quantum principle is taken to overcome the issues of EAs and makes ARQIEA more efficient in comparison to ordinary EAs. The suggested work is arranged in different segments. The first segment provides an introduction to the EELD problem and literature survey. The formation of the Multi-objective EELD problem is provided in the second segment. The third segment introduces the ARQIEA and the application of ARQIEA to solve the EELDP with different test cases given in segment 4. The results are provided in segment five and the conclusion is given in segment six and followed by references.

II. FORMATION OF MULTI-OBJECTIVE ECONOMIC AND EMISSION DISPATCH PROBLEM (MO-EELDP)

The cost of fuel depends upon the amount of total power generation from the electrical power generating units. The EELD problem is carried out to reduce the cost as a prime objective along with emission reduction as a second objective. The desired objective function is shown in equation (1).

$$f_{cost} = \sum_{j=1}^{N} C_j(PG_j) \quad \text{\$/hr.} \qquad (1)$$

The fuel cost for the N electrical power generating units is given in equation (2) with the cost coefficients of the fuel function. Only the fuel cost ($/hr) is considered in the formation any other cost is not included in the objective function [23]:

$$C_j(PG_j) = x_j + y_j PG_j + z_j PG_j^{\,2} \qquad (2)$$

The second objective in the current work is the Emission reduction function. The emission function is given in equation

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(3). The prime objective in the emission function is to minimization of the emission (ton./hr.) from the generating units.

$$f_{emission} = \sum_{j=1}^{N} E_j(PG_j) \quad \text{ton/hr.} \qquad (3)$$

The emission value and the coefficient of the emission function are provided in equation (4). The emission level of j[th] unit depends upon the emission coefficients of the electrical power generating unit and the level of power produced from the unit.

$$E_j(PG_j) = a_j + b_j PG_j + c_j PG_j^{\,2} + \zeta_j e^{\lambda_j PG_j} \quad (4)$$

CONSTRAINTS

Constraints and Constraint handling is the essential part of the constrained optimization problem. The present work also regarded the constraint of the power-generating units and the system. The constraints are efficiently regarded in the solution of the suggested BI-EELDP.

- Power generation limit constraint: the generating unit must regard the maximum and minimum power generation bounds of the units as provided in the constraint limit. This is a box constraint and the power generation from the unit must remain within the prescribed limit as given in equation (5)

$$PG_j^{\min} \le PG_j \le PG_j^{\max}, \qquad (5)$$

- Power demand Constraint: the power generated from all the electrical power generating units must full fill the demand of the consumers and overcome transmission losses. So, the sum of consumer demand and the transmission losses will be equal to generated power as given in equation (6)

$$\sum_{j=1}^{N} PG_j = P_{demand} + P_{loss} \qquad (6)$$

- Power losses evaluation: Kron's loss coefficients (32) are utilized to evaluate the loss level in the present work. the evaluation of losses is carried out as suggested in equation 7 (23):

$$P_{loss} = \sum_{j=1}^{N}\sum_{j=1}^{N} PG_j B_{1j} PG_j + \sum_{i=1}^{N} B_{0j} PG_i + B_{00}$$

(7)

Cost reduction and emission reduction are two goal functions that are incompatible with one another. So it becomes a very complex and difficult task to solve the BI-EELDP with achieving both objectives. Today researchers are more concerned about emission reduction so the emission objective function also becomes equally important to achieve as the cost reduction function. The emission from generating units contains various kinds of pollutants like carbon particles, CO_2, SO_2, NO_2, and other harmful gases. The awareness of people about these pollutants also compels the utility to reduce the emission. Constraint satisfaction is also important to find an acceptable feasible solution to the problem.

III. PROPOSED BI-OBJECTIVE ADAPTIVE REAL CODED QUANTUM-INSPIRED EVOLUTIONARY ALGORITHM (BO-ARQIEA)

The quantum-inspired evolutionary algorithms (QIEA) were suggested by Narayanan and Moore [33]. The authors solved the traveling salesman problem using the QIEA. A detailed survey on QIEA is proposed in [34] by Gexiang Zhang. The QIEA comes under the family of EAs and is inspired by quantum mechanics principles. It is an algorithm designed to work on classical computers. The QIEA is much more advanced than ordinary EAs due to the magical impact of Qubits, quantum principles in solving an optimization problem with the probabilistic nature of the qubits [34-36]. The adaptation of different user choice-based operators makes the QIEA more effective [25]. The QIEA can handle the issues of convergence, diversity, parameter tuning, etc. as faced by the EAs.

The present work chose to apply an enhanced variant of QIEA named multi-objective adaptive real coded quantum-inspired evolutionary algorithm (MO-ARQIEA) due to several advantages and effective application of QIEA and its other variants in different works [37-57]. A problem of ceramic surface grinding is solved using an adaptive real-coded quantum-inspired evolutionary algorithm (ARQIEA) [37] in a constrained environment. An efficient quantum gate rotation methodology suggested in [38] for AQIEA is based on the Taguchi method. A complex task for optimal placement of distributed generators (DGs) is accomplished in [39] using AQIEA. A reconfiguration of a distribution network is carried out to reduce losses and improve the voltage regulation in [40] using the adaptive real-coded quantum-inspired evolutionary algorithm. An approach of loss reduction is utilized in [41] to reduce the power losses using AQIEA. A combined approach of DGs placement and network reconfiguration is used [42] using a similar solution algorithm as suggested in [39]. The optimal placement of the capacitor [43], DGs placement [43] capacitor sizing calculation [45], and power reduction approach [45] are used by similar authors using the AQIEA. The problem of unit commitment (UC) and ELDP using [QIEA] in [46], UC using improved QIEA (QIEA) in [47], and UC is solved in [52, 54] using QIEA. An advanced variant of QIEA named multipartite adaptive binary-real quantum evolutionary algorithm to solve the various case of unit commitment problems under a constrained environment [56-57]. A process of image registration based on multiple sensors is solved in [48] using a novel QIEA. An approach to the economic operation of a smart grid is suggested in [49] using a fuzzy advanced QIEA.

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A power dispatch (real and reactive power) is solved using QIEA [50]. A knapsack problem is solved using a multi-objective approach of QIEA [51]. An AQIEA is used to solve the multi-objective optimization problem [53] and the ELD problem is solved [55] using the same algorithms. An advanced variant of QIEA named multipartite adaptive binary-real quantum evolutionary algorithm to solve the various case of unit commitment problems under a constrained environment [56-57]. The literature on the above application of QIEA, AQIEA, and other enhanced variants of QIEA, drags the author's attention to the uses of ARQIEA in the current work.

The results and effectiveness of these algorithms on different problem motivates us to use the MO-AQIEA in the present work. The present algorithm is advanced from the ordinary QIEA in different ways. The current approach used two sets of qubits instead of single qubits as used in QIEA. The EELD problem is solved by applying quantum principles and combining an adaptive quantum-inspired evolutionary algorithm (AQIEA) [25] with a non-dominated sorting strategy from NSGA -II [24]. A similar methodology is also used in [26].

MO-ARQIEA is inspired by the quantum principles like entanglement, interference, measurement, and superposition principles. The role of these principles and other parameters is defined below.

Qubit: this is the prime and smallest unit of information. It stores the value in the form of (0, 1). All the principles and quantum operations are performed on the qubits. It is similar to the classical bit but there is a major difference between them. The qubit has probabilistic nature and it stores the values the between (0 and 1). Under the superimposed state it may be shown as [25]:

$$|\Psi> = A|0> + B|1> \tag{8}$$

Where, $|A|^2$ and $|B|^2$ is the probability amplitude of the qubit for the two different states as $|0>$ and $|1>0$ with the Below given states of affair should be satisfied:

$$|A|2 + |B|2 = 1 \tag{9}$$

Superposition principle: under the influence of this principle the individual particle attains all possible states (0 and 1) and in between (0 and 1).

Measurement Principle: this principle is used to measure the state of any quantum particle when it is under superimposed state both (0 and 1) or in between (0 and 1).

Interference Principle: it defines the state of the quantum particle due to the natural ability of a particle to attain any state under a superimposed operator and the final possibility to attain either 0 or 1.

Entanglement Principle: under the influence of this principle the two or more qubits show an entangled relation. Whenever any operation is performed on any qubit it just does not change the state of that particular qubit only but also changes the value of all other qubits which are entangled with the first qubit.

Q-Bit register: the qubits are stored in the quantum register. The structure of the qubit register is shown below:

$$RQ1, K = [\alpha1,1,K, \alpha1,1,K,\ldots\ \alpha1,1,M,]$$
$$RQ1, L = [\alpha1,L,1, \alpha1,L,1\ldots\ \alpha1,L,M,]$$
$$RQ1, 20M = [\alpha1, 20,1, \alpha1, 20,2, \ldots\ \alpha1, 20,M,] \tag{10}$$

The present MO-ARQIEA uses two sets of the qubit. The first qubit holds the objective function, input parameters, and scaled values of the variables. The second qubit stores the ranked and scaled values of all the solution vectors for every iteration. Both of the qubits are entangled in such a way that in every iteration value of the qubit is changed then the value of the second qubit changes accordingly. The first qubit uses and decides the probabilistic value of the second qubit. The number of qubits in a quantum register is always equal to the number of the variable used. The number of the quantum register is generally in the multiple of 100 times variables used in the problem. Several iterations are carried out and the fittest feasible solution is ranked and stored in the second qubits [25].

An adaptive crossover operator (ACO) is also used in the suggested work to carry out parameter-free tuning with gate rotation methods. An efficient balance between exploitation and exploration is maintained. The gate rotation method moves the solution vectors towards achieving the best possible fittest value. In the next three rotational techniques in the current study, RG-I rotates solution vectors in the direction of the best solution, RG-II spins them away from the worse solution, and RG-III rotates them in the direction of the best solution [40]. The first qubit's angle of rotation is established using the probabilistic value of the second qubit [25].

$$\psi1i(m+1) = \psi1i(m)+f(\psi2i(m), \psi2j(m)) * (\psi1j(m)- \psi1i(m)) \tag{11}$$

In the case when m is the generation number and $\psi1j$ is the fittest vector, the vector may be selected at random otherwise.

The present approach also uses multitudinous attractors in RG-II, which may be named RG-IIA. Constraint handling is an important and necessary part of optimization. A detailed study of various constraint handling methods is carried out before selecting the constraint handling method for the present work as provided in [62-68] A repair-based novel operator has been originated that makes certain that spinning reserve constraints are always fulfilled [60-61].

IV. APPLICATION OF BO-ARQIEA ALGORITHM ON TEST CASES

The pseudo-code is as follows:

Random Initialization (RQ1)
While (terminate_ criteria) {

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Apply repair (RQ1)
Fitness calculation = Calculate _fitness of (RQ1)
Fitness calculation = Calculate _fitness of (RQ2)
Sorting = RQ2A (non-dominated sorting)
Ranking &Scaling= rank _scale RQ2B
Apply AQCO= Produce _Children (RQ1, RQ2)
Selection= Tournament selection (binary) (RQ1, children RQ1)

Description of steps

Step 1: initialize the Quantum register RQ1 and assignee value (0, 1) randomly. Load the input data of generating units.
Step 2: Apply the repair method to repair individuals to satisfy constraint limits including different parameters like maximum and minimum power, load demand, etc. evaluate the constraint violation and balance the violation.
Step 3: Calculate the fitness function of solution vectors.
Apply the approach of non-dominated sorting and evaluate RQ2A.
Step 4: Compute ranked and scaled values of RQ2B.
Step 5: Apply ACO operator and gate rotation strategy.
Step 6: Determine the rotation direction and angle using QR2 and QR1.
Step 7: Generate a new generation using ACO.
Step 8: repeat iteration till termination criteria meet.

TEST CASES

The present work considers the IEEE (30-bus) system along with six power-generating units to evaluate the effectiveness of the suggested algorithm (BO-ARQIEA). Similar test case systems (C1 and C2) are also used in [24], [27] and test case systems (C3 and C4) are adopted from the [65]. The suggested algorithm is verified on the following test cases:

1. Test case system (C1) for the best cost($/hr) and best emission (ton./hr.) Considering six generating units
2. Test case system (C2) for the best cost ($/hr) and best emission (ton. /hr.) Considering six generating units.
3. Test case system (C3) for the best cost ($/hr) and best emission (ton. /hr.) Considering six generating units (500 MW).
4. Test case system (C4) for the best cost ($/hr) and best emission (ton. /hr.) Considering six generating units (700 MW).

The test cases C1 and C2 are adopted from [24] and the loss coefficients are adopted [23] as used in equation (7). The total number of qubits registers is 300 in the present work. The Fitness evaluation limitation for the C1 and C2 are respectively 10000 and 20000. The suggested approach is not used a diversity operator but this is capable to achieve an efficient Pareto front as provided in Fig. 1 and Fig. 2 for the cases C1 and C2.the outcomes received are compared with a different well-known algorithm like NSGA [28], NPGA [29], SPEA [30], NSGA – II [24] SOS [65], BBO [66], FCGA [67], BGO [68], and MOSST [31], Algorithms as shown in Table 1 and Table 2 for Case C1.

V. RESULTS

The results for all of the aforementioned test case systems obtained after using the proposed MO-ARQIEA are displayed in various tables (Tables 1 through table 8). (C1, C2, C3, and C4). Results for the test case system C1's best cost case are shown in Table 1, and results for the test case system C1's best emission scenario are shown in Table 2. The outcomes are contrasted with those of other widely used solution methodologies. Although the solution is not widely dispersed, MO-ARQIEA does a good job of maintaining the solution's variety.

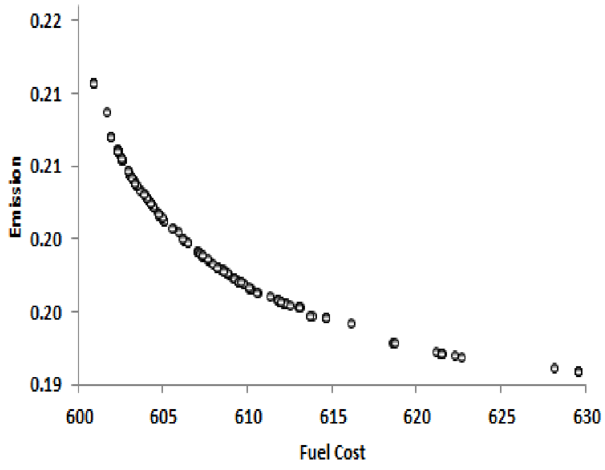

Fig. 1. the solution obtained by MO-ARQIEA (Non-dominated) for CASE C1

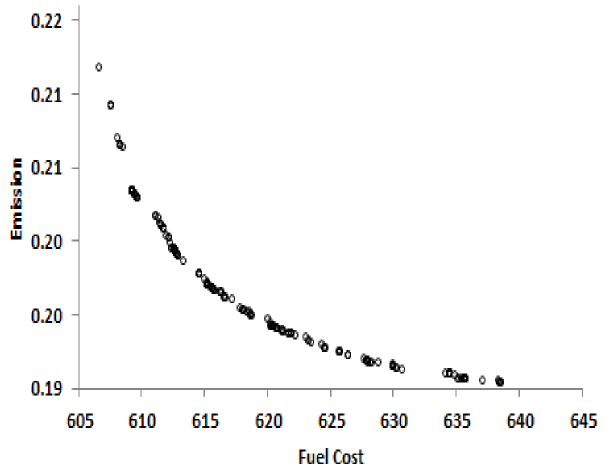

Fig. 2. the solution obtained by MO-ARQIEA (Non-dominated) for CASE C2

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Table 3 shows the results for the best cost for the test case system C2. Table 4 shows the best emission results for the test case system C2. The results are compared with various algorithms NSGA [28], NPGA [29], SPEA [30], NSGA-II [24], BBO [66], and BGO [68]. The findings for the test case system C3's best cost are displayed in Table 5. The test case system C3's top emission results are displayed in Table 6. Several algorithms, including NSGA [28], FCGA [67], NSGA-II [24], BBO [66], and SOS [65], are used to compare the results.

Table 7 shows the results for the best cost for the test case system C4. Table 8 shows the best emission results for the test case system C4. The results are compared with various algorithms FCGA [67], NSGA-II [24], BBO [66], and SOS [65].

TABLE 1: RESULT FOR COST REDUCTION FOR CASE C1 (BEST FUEL COST)

	MOSST [31]	NSGA [28]	NPGA [29]	SPEA [30]	NSGA-II [24]	MO-ARQIEA
TG 1	0.1125	0.1567	0.1080	0.1062	0.1059	0.1045
TG 2	0.3020	0.2870	0.3284	0.2897	0.3177	0.2995
TG 3	0.5311	0.4671	0.5386	0.5289	0.5216	0.5173
TG 4	1.0208	1.0467	1.0067	1.0025	1.0146	1.0122
TG 5	0.5311	0.5037	0.4949	0.5402	0.5159	0.5376
TG 6	0.3625	0.3729	0.3574	0.3664	0.3583	0.3628
Best cost ($/hr.)	605.889	600.572	600.259	600.15	600.155	600.123
Corresp. Emission (ton./hr.)	0.22220	0.22282	0.22116	0.2215	0.22188	0.2221

TABLE 2: RESULT FOR EMISSION FOR CASE C1 (BEST EMISSION)

	MOSST [31]	NSGA [28]	NPGA [29]	SPEA [30]	NSGA-II [24]	MO-ARQIEA
TG 1	0.4095	0.4394	0.4002	0.4116	0.4074	0.4061
TG 2	0.4626	0.4511	0.4474	0.4532	0.4577	0.4591
TG 3	0.5426	0.5105	0.5166	0.5329	0.5389	0.5380
TG 4	0.3884	0.3871	0.3688	0.3832	0.3837	0.3830
TG 5	0.5427	0.5553	0.5751	0.5383	0.5352	0.5379
TG 6	0.5142	0.4905	0.5259	0.5148	0.5110	0.5100
Best Emission (ton./hr.)	0.19418	0.19436	0.19433	0.1942	0.19420	0.19420
Corresp. Cost ($/hr.)	644.112	639.231	639.182	638.51	638.269	638.274

TABLE 3: BEST FUEL COST FOR CASE C2

	NSGA [28]	NPGA [29]	SPEA [30]	NSGA-II [24]	BBO [66]	BGO [68]	MO-ARQIEA
TG 1	0.1168	0.1245	0.1086	0.1182	0.0500	0.1180	0.0500
TG 2	0.3165	0.2792	0.3056	0.3148	0.4000	0.3053	0.2536
TG 3	0.5441	0.6284	0.5818	0.5910	0.6875	0.6249	0.6136
TG 4	0.9447	1.0264	0.9846	0.9710	0.9500	0.9588	1.0547
TG 5	0.5498	0.4693	0.5288	0.5172	0.5500	0.5915	0.5962
TG 6	0.3964	0.3993	0.3584	0.3548	0.2309	0.3503	0.2922
Total Power Output	2.8683	2.9271	2.8678	2.867	2.8685	2.9488	2.8603
Power Loss	0.0343	0.0931	0.0338	0.033	0.0345	0.1148	0.0263
Best cost ($/hr.)	608.245	621.5644	607.807	607.801	612.334	626.395	607.645
Corresp. Emission (ton./hr.)	0.21664	0.22364	0.22015	0.21891	0.223369	0.21878	0.23022

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TABLE 4: BEST EMISSION FOR CASE C2

	NSGA [28]	NPGA [29]	SPEA [30]	NSGA-II [24]	BBO [66]	BGO [68]	MO-ARQIEA
TG 1	0.4113	0.3923	0.4043	0.4141	0.410500	0.408881	0.4056
TG 2	0.4591	0.4700	0.4525	0.4602	0.463289	0.461795	0.4650
TG 3	0.5117	0.5565	0.5525	0.5429	0.543820	0.541602	0.5499
TG 4	0.3724	0.3695	0.4079	0.4011	0.389949	0.387349	0.3886
TG 5	0.5810	0.5599	0.5468	0.5422	0.544118	0.541801	0.5463
TG 6	0.5304	0.5163	0.5005	0.5045	0.515173	0.513311	0.5135
Total Power Output	2.8659	2.8645	2.8645	2.865	2.866849	2.854739	2.8689
Power Loss	0.0319	0.0305	0.0305	0.031	0.032849	0.020739	0.0349
Best Emission (ton./hr.)	0.19432	0.19424	0.19422	0.19419	0.194179	0.194186	0.19418
Corresp. Cost ($/hr.)	647.251	645.984	642.603	644.133	645.6366	642.9249	645.932

TABLE 5: BEST FUEL COST FOR CASE C3 (500 MW)

	NSGA-II [24]	FCGA [67]	BBO [66]	SOS [65]	MO-ARQIEA
TG 1	50.86	49.47	50.58329	50.5853	50.04352
TG 2	31.806	29.4	30.30182	30.3062	30.39399
TG 3	35.12	35.31	35.00089	35.00	35
TG 4	73.44	70.42	71.7444	71.7455	72.14708
TG 5	191.988	199.030	195.24314	195.2382	195.3311
TG 6	135.019	135.220	135.60388	135.6009	135.6616
Total Power Output	518.209	518.85	518.47742	518.4738	518.57726
Power Loss	18.209	18.85	18.4738	18.4738	18.57726
Best cost ($/hr.)	28150.86251	28150.25591	28149.25943	28149.13533	28148.87383
Corresp. Emission (ton./hr.)	309.040318	314.5229968	311.7950199	311.7893175	311.7763965

TABLE 6: BEST EMISSION FOR CASE C3 (500 MW)

	NSGA-II [24]	FCGA [67]	BBO [66]	SOS [65]	MO-ARQIEA
TG 1	56.931	81.08	57.40627	57.4008	57.71465
TG 2	41.542	13.93	44.44419	44.4264	44.82106
TG 3	73.896	66.37	76.03817	76.0771	75.8797
TG 4	84.931	85.59	84.43863	84.4182	84.42277
TG 5	136.502	141.7	134.3981	134.4163	134.0109
TG 6	131.328	135.93	128.8418	128.8419	128.6197
Total Power Output	525.13	524.6	525.5671	525.5807	525.4688
Power Loss	25.13	24.6	25.56709	25.5807	25.46878
Best Emission (ton./hr.)	275.5444	286.5870035	275.3854062	275.3886894	275.3808098
Corresp. Cost ($/hr.)	28641.13	28756.4994	28706.59138	28706.90169	28711.28205

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TABLE 7: BEST FUEL COST FOR CASE C4 (700 MW)

	NSGA-II [24]	FCGA [67]	BBO [66]	SOS [65]	MO-ARQIEA
TG 1	76.179	72.14	73.95336	73.9386	74.06864
TG 2	51.81	50.02	50.35537	50.3639	50.72647
TG 3	49.82	46.47	45.79807	45.8163	46.43572
TG 4	103.407	99.33	104.059	104.023	103.7366
TG 5	267.984	264.6	270.7745	270.8317	268.9035
TG 6	184.734	203.58	189.7032	189.6709	190.6674
Total Power Output	733.934	736.14	734.6435	734.6444	734.5383
Power Loss	33.934	36.14	34.64347	34.6444	34.53827
Best cost ($/hr.)	38370.75405	38383.89818	38364.42875	38364.42731	38359.46858
Corresp. Emission (ton. /hr.)	534.924644	543.4685497	543.3733898	543.4094078	541.0329175

TABLE 8: BEST EMISSION FOR CASE C4 (700 MW)

	NSGA-II [28]	FCGA [67]	BBO [66]	SOS [65]	MO-ARQIEA
TG 1	103.078	120.16	104.4574	104.3456	103.645
TG 2	73.505	21.36	77.78433	77.8036	77.40206
TG 3	91.556	62.09	93.51512	95.5137	93.59586
TG 4	110.787	128.05	110.9113	110.8788	111.4225
TG 5	187.869	209.65	185.5126	185.6437	186.0831
TG 6	174.289	201.12	169.8277	169.8192	169.8602
Total Power Output	741.084	742.43	742.0085	744.0046	742.0088
Power Loss	41.084	42.43	42.00848	44.0046	42.00877
Best Emission (ton. /hr.)	467.3886962	516.5474996	467.0347446	468.5260487	466.9628977
Corresp. Cost ($/hr.)	39473.44945	39454.84581	39628.84477	39717.4206	39601.77518

VI. CONCLUSIONS

The prime aim of the cost reduction and emission reduction is achieved using the multi-objective Adaptive Real Coded Quantum inspired evolutionary algorithm to solve a MOEELD problem. The effectiveness of the suggested algorithm is tested on different test case systems efficiently in a constrained environment. Both objectives having opposite natures are achieved efficiently by gratifying all the constraints using repair-based constraint handling. The result proves the capability of the algorithm in solving the constrained MO-EELD problem on the IEEE 30 bus system consisting of six generating units. The results are found impressive in comparison with other well-known state of art algorithms. Further work will be carried out using ARQIEA on different benchmark problems along with various test cases.

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