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Multi-Objective Evolutionary Programming for Solving Economic Dispatch Problem

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ABSTRACT

Economic dispatch (ED) is an optimisation strategy to ensure power systems operate in an economic manner. This paper proposes a multi-objective optimisation method to minimise the total generation cost and total system loss simultaneously and find the best adjustment for this economic dispatch problem. This study focused on solving the multi-objective economic dispatch problem using a Heuristic Optimisation (HO) method, namely Multi-Objective Evolutionary Programming (MOEP). The Weighted Sum Method (WSM) is integrated with EP to find a trade-off solution between two objectives: total generation cost minimisation and total system loss minimisation. The practicable proposed method was tested on the IEEE 30-Bus Reliability Test System (RTS) for three different scenarios. MATLAB programming language was used to run the designated algorithm of MOEP. The performance of MOEP to solve the multi-objective ED problem was then compared with another method; the Multi-Objective Artificial Immune System (MOAIS). The experimental results show that MOEP dominates in all cases that have been tested, proving that MOEP is superior than MOAIS in providing high-quality solution to economic dispatch problem with multiple objectives in terms of cheap total generation cost and low total system loss.

Key words : Economic dispatch, evolutionary programming, multi-objective optimisation, weighted-sum method.

1. INTRODUCTION

Throughout the present increasingly sophisticated era of technology, one of the abiding issues in power system operations and power generation is to find the most efficient solution to Economic Dispatch (ED) problem. Generally, economic dispatch is a subroutine of unit engagement, for which the objective is to identify ideal generator outputs so that the entire load can be delivered in the most economical manner. This goal has been an issue for power system networks for many years, with many methods being advanced as a solution [1]-[6]. Put simply, the problem is to minimise the generation cost produced by each of the generator outputs. In addition to the generation cost, increasing transmission loss in systems also remains an issue requiring optimisation for the the smooth running of power systems.

Indeed, the problem can be summarised in the following scenario: a system which consists of a quantity of generators serving an electrical load in a system which uses multiples types of fuel input consuming at high generation cost to operate power plants such as Hydro, Gas, Steam Diesel, Nuclear, Coal, Solar, Wind, etc [7]. Ideally, the power systems should be operated with the highest quality performance and as economically as possible; at the lowest generation cost. In order to minimise generation cost, a specific function is required that will extract the output produced by the generators. As mentioned in [8], to find the value of generation cost a quadratic equation was developed by previous researchers to form a value for the thermal generator output. Next, while acquiring the value of total generation cost, the transmission losses can also be obtained in the power system from the *B* loss coefficients which are approximately considered as a quadratic function of the real power generation [9]–[16].

HO methods are considered compatible with current power systems for solving their economic dispatch problem. HO methods are more advanced than mathematical methods like linear programming and quadratic programming in terms of searching for the global optima of optimisation problems. HO methods include: Genetic Algorithm (GA), Evolutionary Strategy (ES) [17], Evolutionary Programming (EP) [18], Particle Swarm Optimisation (PSO) [19], Simulated Annealing (SA) [20] Artificial Immune System (AIS) [21], [22], etc. Methods such as these are usually an improved version which are adapted to handle highly nonlinear economic dispatch problem with any kind of shape of cost curve [23]. HO methods do not rely on the calculation of derivatives such as gradient vectors or Jacobian/Hessian matrices, where non-convexity and non-differential problem might have an effect [24].

This paper proposed the use of the Heuristic optimisation method to solve ED problem in power systems with multiple objectives. Although there are various types of Heuristic optimisation methods, EP was chosen for this study to develop an algorithm that will satisfy all constraints, functions and to provide the most optimised result for ED problem with multiple objectives. EP has proven to be a powerful method to solve many power system optimisation problem. EP is a probabilistic, worldwide search method that starts with a population of randomly-produced candidate solutions and evolves over a number of generations or iterations towards superior alternatives [25]. Initialisation, mutation, competition and choice are the primary phases of this method; a method which is considered one of the most widely recognised methods for producing the best results for ED. EP was integrated with WSM to solve ED problem with multiple objectives. The objectives are to minimise total production cost and to minimise total system loss. This proposed method is named as Multi-Objective Evolutionary Programming (MOEP). ED solution produced via MOEP was compared with non-optimised power system and Multi-Objective Artificial Immune System (MOAIS) method. And MOEP successfully outperformed MOAIS in giving the best ED solution in terms of low total generation cost and low total system loss for the IEEE 30-Bus RTS.

2. PROBLEM FORMULATION OF MULTI-OBJECTIVE ECONOMIC DISPATCH

The main problem for this study is to reduce the total generation cost and total system loss of the power system, which for this study is the IEEE 30-Bus RTS. Formulas of ED such as cost function, power losses function and constraints and are needed in order to solve this multi-objective ED problem. All the required objective functions and constraints equations of the ED problem and equations of the proposed MOEP method are explained in this section.

2.1 Cost Function

Equation 1 shows the cost function, expressed as a single quadratic function in terms of real power output and cost coefficients (δ, η, ξ). The cost of each generator will be summed up to arrive at a total value of cost for optimisation purposes, as shown in Equation 2.

$$Ci(Pgi) = \delta i + \eta i Pgi + \xi i Pgi^2 \qquad (1)$$

$$\min F_1 = C_s = \sum_{i=1}^{n} C_i(Pg_i) \qquad (2)$$

Where:

δ_i, η_i, ξ_i = the thermal generator's cost coefficients of the *ith* generator

n = total number of generators

Ci = cost of the *ith* generator

Cs = total generation cost

Pgi = real power output of the *ith* generator

:

2.2 Losses Function

The second objective of this study is to minimise the total system loss for the transmission system. The total system loss is also known as transmission losses that can be expressed by Equation 3 and Kron's loss formula in Equation 4. B is defined as a loss matrix, B_0 as a loss coefficient vector and B_{00} as a constant of loss coefficient. By using the Hadi Saadat load flow program, total system loss in the test system is automatically calculated by certain commands in MATLAB and the obtained value can then be combined with the total generation cost in a single equation for multi-objective optimisation.

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \qquad (3)$$

$$\min F_2 = P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \qquad (4)$$

Where:

P_L = power losses

n = total number of generators

B = loss coefficient for a network branch

i, j = power generation and production units

2.3 Constraints

There are a few constraints which needed to be fulfilled for this study in order to make the power system run economically and efficiently; namely, an equality constraint and an inequality constraint. For solving quadratic equations, it is possible to use the equality constraint, which in this study was the real power balance constraint, while the generator limit constraint would represent the inequality constraint. Equation 5 represents the real power output of each generator, confined by the lower and upper boundaries in order to guarantee stable operation; limits which are also usually known as problem boundaries. The balance of power is a constraint that confines the power system to a fundamental principle of equilibrium among both total system generation and total system loads. The total power of the generation must, therefore, be equal to the sum of power demand and power losses to balance the power inside the generation which is expressed in Equation 6.

$$P_i^{min} \leq P_i \leq P_i^{max} \qquad (5)$$

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \tag{6}$$

Where:

P_i^{min}	=	lower limit for generator power of *ith* unit
P_i^{max}	=	upper limit for generator power of *ith* unit
P_D	=	power demand
P_L	=	power losses
n	=	total number of generators
i	=	unit of generators

2.4 Penalty Factor

By definition, the penalty factor, Qm is the ratio between maximum cost and maximum losses in a power system. This study aimed at solving multi-objective ED problem in which the penalty factor would be placed inside the Weighted Sum Method (WSM) to provide better optimised results. The implementation of the penalty factor would be executed by taking the highest cost and highest losses produced by using the maximum limit of the generators, as shown in Equation 7.

$$Qm = \frac{Fx(max)}{Fy(max)} \tag{7}$$

Where:

$Fx(max)$	=	maximum total generation cost
$Fy(max)$	=	maximum total system loss
Qm	=	penalty factor

2.5 Weighted Sum Method

The combination of both objectives into a single objective was essential for this study, where both objectives needed to be minimised simultaneously. WSM was able to solve this problem by weighting both objective functions according to relative requirement and both weighted functions would be added together to produce a single objective function as shown in Equation 8. From the equation, values of F_a would be in the range 0 until 1. When F_a is 0, only the power losses function is optimised and when F_a is 1, only the cost function is optimised. A trade-off between the cost and the power losses function would be determined by the varying value of F_a which would provide the best solution for this optimal dispatch problem.

$$MO = F_a F_x + (1 - F_1)(Qm)F_y \tag{8}$$

Where:

F_x	=	cost function
F_y	=	power losses function
MO	=	multi-objective function
F_a	=	weighting coefficient (vary from 0 to 1)

3. MULTI-OBJECTIVE EVOLUTIONARY PROGRAMMING (MOEP)

EP is a population-based algorithm that begins with a population produced randomly and evolves over a number of iterations towards finding ideal alternative solutions. The EP algorithm works straight over the alternatives through tiny mutations and utilises an elitist-based selection method. Solutions are described as generation values for all units within the system and are originally identical with earlier run unit engagement algorithm's pre-dispatch values. Furthermore, EP can minimise and maximise any fitness, which can be implemented by mathematical equations. The fitness function evaluates the quality of the suggested solution that sets the foundation for the method of choice. EP will produce a result after a convergence criterion is met and all of the constraints have been followed. There are three types of EP: Classical EP (CEP), Fast EP (FEP) and Improved Fast EP (IFEP). Mutation is a very significant part of EP and these three types of EP use different techniques of mutation. CEP uses a Gaussian operator for the mutation part while FEP uses a Cauchy operator where it converges quicker than CEP. For IFEP, the mutation part runs using a combination of Gaussian and Cauchy operatorship, composed at a higher rate of convergence compared to CEP and FEP. However, for this study, CEP was selected as the method is easier to understand and any solution produced would, therefore, be clearer and more easy to implement. The steps of EP are listed below, steps which impose critical functions that are very important for achieving the most successful result for EP:

- Initialisation
- Fitness (1) Computation
- Mutation
- Fitness (2) Computation
- Combination
- Selection
- Convergence Test

3.1 Initialisation

The initial population was generated containing combinations of the candidate-only dispatch alternatives that meet all the constraints. The population was randomly generated from the range of minimum and maximum generator values allowed, based on inequality constraints. This was applied to all generators at bus 2, 5, 8, 11, and 13 where bus 1 is considered a slack bus. Bus 1 would be calculated using the Newton-Raphson method where the value would fulfil the remaining value left to obey the equality constraint. The random values are called trial parent individuals (*I*) in the EP method.

3.2 Fitness Computation

In an EP algorithm, fitness can be defined as a single mathematical equation or a long subroutine. Fitness applies to the equation, function or subroutine that needs to be optimised. Fitness, therefore, applies in this study to the objective functions which are cost function and losses function, with the addition of WSM, required for MOEP, as it is a WSM equation. There would, of course, be minimum and maximum fitness values, which are restricted by the constraints used. The fitness process would generate offspring individuals that have been transferred from parent individuals (I) from the initialisation process.

3.3 Mutation

The mutation process has three different techniques for each type of EP. Classical EP (CEP) approach of mutation was chosen to produce the new generation of population which the mutation process uses Gaussian operator to mutate the parent population. In this process, each vector component has the mutation process in which a normally distributed random number with a mean of zero and standard deviation is added, which is denoted as $N\left(0, \sigma_j^2\right)$. The values of objective functions for both offspring would be obtained before proceeding to the evaluation and comparison stages. In this way, the best individual selected from all of the stages would be represented as an offspring for the next step. The output from this stage would then become another fitness output which also consists of 20 populations. Put simply, parents from the previous step would breed (mutation process) and produce children called offspring. Both parents and offspring would then compete with each other to become the best output for the next step.

3.4 Selection

The classification processes for to solve the ED issue are to find the non-dominated alternative in the present *2I* population (parents and offspring) using all of the calculated finesses. A rank would be assigned for the solutions by counting the amount of solutions that outperform every situation. The rank assigned to each solution would then sort the *2I* solutions into the ascending order. Hence, the first I solutions were chosen as parents and the next generation would be defined without their rank values in terms of rows and columns. Ranking, for this of selection process, would be sorted by putting the minimum fitness at the highest order and the maximum fitness will be placed at the lowest order. After that, new generation is defined for the convergence test.

3.5 Convergence Test

After each new generation was defined from the previous process, the values would undergo a convergence test to define minimum and maximum fitness by listing the 20 best values in rows and columns. The convergence test would converge only after the stopping criterion was met. The stopping criterion for this MOEP algorithm was equal to 0.00001. If the test failed to converge, the mutation and selection process would be repeated until the maximum generation number was reached to terminate the iteration process. The solution would converge only after the objective function and fitness were the same for all populations. The number of iterations could only be determined when the solution converged. The output for this stage would represent the best solution for the optimisation of ED problem.

4. RESULTS AND DISCUSSION

The IEEE 30-Bus RTS with six generators was used for implementing the proposed method for solving the ED problem. This test system consisted of thirty buses equipped with six generators located at buses 1, 2, 5, 8, 11 and 13. While Bus 1 could be considered a slack bus, buses 2, 5, 8, 11 and 13 were the generator buses. The balance of the other buses could be considered load buses. Figure 3.1 illustrates the sample model of the test system used.

The proposed solution was executed via EP method that was developed using MATLAB. WSM was applied to optimise both objectives simultaneously with the addition of penalty factor. WSM would vary the equation using a weighing factor (F_a) from 0 to 1, where each value of F_1 would produce values for total generation cost and total system loss. Two criteria needed to be considered for the best solution: the lowest value and the fastest CPU time. Three different case studies were introduced in this study. Case Study 1 was a normal operation (without any increment), while for Case Study 2 and 3 the load was increased to 50 % and 70 %, respectively, as the increment would affect the value of total power demand (PDT). EP was developed to optimise ED problem and the algorithm was integrated with Hadi Saadat's power system load flow program of the IEEE 30-Bus RTS in MATLAB software. The results produced by this method were then compared with a non-optimised power system and the final results were produced via the Artificial Immune System (AIS) method. The purpose of the comparison was to show that EP is a superior method for optimising multi-objective ED problem. All parameters and constraints were set equally for both methods.

4.1 Case Study 1: Normal Load Operation

Values of total generation cost and total system loss from the non-optimised power system were recognised as base values. The base value for total generation cost was 875.40 $/h, while the total system loss was 17.60 MW. Furthermore, the penalty factor, Qm value inside the WSM equation was equal to 0.2389. Table 1 shows the optimised result for the first case of MOEP. From the table, it is clear that the lowest value of total generation cost and total system loss were generated when the weighing factor was at F_a equal to 0 until 0.7. Total generation cost and total system loss found via MOEP with 0.7 weighing factor were 866.60 $/h and 5.39 MW respectively. Based on the criteria, the values produced when F_a was equal to 0.7 were the best option to minimise both objectives where the CPU time taken was the fastest among the other results that consumed six iterations.

Table 1: ED Result via MOEP for Case Study 1

Weighing Factor, F_1	Total System Loss (MW)	Total Generation Cost ($/h)	CPU time (s)	Iteration
0.0	5.39	866.60	8.921419	9
0.1	5.39	866.60	9.673227	9
0.2	5.39	866.60	9.052752	8
0.3	5.39	866.60	8.181559	8
0.4	5.39	866.60	8.858250	8
0.5	5.39	866.60	8.071019	7
0.6	5.39	866.60	7.563589	7
0.7	5.39	866.60	7.484498	6
0.8	6.08	802.10	6.474046	6
0.9	6.08	802.10	7.391302	6
1.0	8.97	787.60	7.694458	6

4.2 Case Study 2: 50% Load Increment

In Case Study 2 the value of PDT was increased by 50%, which affected the base value for the total generation cost and total system loss. The base values for both objectives were 1654.20 $/h and 45.44 MW. The result of this case study is tabulated in Table 2. The penalty factor, Qm was equal to 0.0864 for this case. It can be seen from the table that the best solution of ED was found when F_a was set to 0.7 which were 19.27 MW and 1394.70 $/h for total system loss and total generation cost respectively. This is based on the values of the two objectives satisfied each other. Compared to when F_a was equal to 0 until 0.6 and F_a was equal to 0.9 until 1.0. Although the values of the total system loss and total generation cost are the same with when F_a was equal to 0.8, but the CPU time was faster for F_a equal to 0.7.

Table 2: ED Result via MOEP for Case Study 2

Weighing Factor, F_1	Total System Loss (MW)	Total Generation Cost ($/h)	CPU time (s)	Iteration
0.0	19.27	1394.70	14.585223	8
0.1	19.27	1394.70	14.684424	8
0.2	19.27	1394.70	16.609822	8
0.3	19.27	1394.70	13.347557	7
0.4	19.27	1394.70	13.507548	7
0.5	19.27	1394.70	13.473950	6
0.6	19.27	1394.70	11.951955	6
0.7	19.84	1373.00	12.713393	6
0.8	19.84	1373.00	12.789038	6
0.9	21.58	1352.40	12.038246	6
1.0	21.58	1352.40	12.377625	6

4.3 Case Study 3: 70% Load Increment

PDT was increased by 70% for this case. The base values for both objectives also automatically increased where the values were 2055.10 $/h for total generation cost and 481.78 MWh for total system loss. Table 3 shows all the results obtained for this case. The penalty factor Qm calculated for this case was equal to 0.0667. Unlike in case study 1 and case study 2, it can be seen that MOEP produced the same values of total system loss and total generation cost for all values of F_a. Therefore, F_a equal to 0.6 was considered as the best solution for both objectives based on its fastest CPU time which was 12.567457 s. The total system loss and total generation produced for this case were 27.00 MW and 1632.50 $/h.

Table 3: ED Result via MOEP for Case Study 3

Weighing Factor, F_1	Total System Loss (MW)	Total Generation Cost ($/h)	CPU time (s)	Iteration
0.0	27.00	1632.50	15.461241	8
0.1	27.00	1632.50	15.263331	8
0.2	27.00	1632.50	15.493620	8
0.3	27.00	1632.50	14.070168	7
0.4	27.00	1632.50	15.365154	7
0.5	27.00	1632.50	15.912519	7
0.6	27.00	1632.50	12.567457	6
0.7	27.00	1632.50	13.411568	6
0.8	27.00	1632.50	13.383327	6
0.9	27.00	1632.50	15.536478	6
1.0	27.00	1632.50	15.460824	6

4.4 Comparison of Multi-Objective Methods

A comparison between MOEP, Multi-Objective Artificial Immune System (MOAIS) and the non-optimised power system was performed to prove the good quality of MOEP. Table 4 presents the ED results taken from the non-optimised power system, MOEP and MOAIS methods for the normal load condition (case study 1). The total generation cost and total system loss produced by MOEP were lower than by MOAIS and non-optimised power system which were 866.60 $/h and 17.60 MW respectively. Furthermore, MOEP optimally distributed the generation between the generators to give the better solution of ED.

Table 4: Comparison of ED Results for Normal Load

Method		Non-Optimised	MOAIS	MOEP
Generator Real Power Output (MW)	P_{g1}	261.00	123.23	112.28
	P_{g2}	40.00	45.84	63.52
	P_{g5}	0.00	29.13	49.98
	P_{g8}	0.00	34.68	32.21
	P_{g11}	0.00	29.34	14.66
	P_{g13}	0.00	27.01	16.13
	$P_{g(total)}$	301.00	289.22	288.79
	PDT	283.40	283.29	283.34
Total Generation Cost ($/h)		875.40	869.87	866.60
Total System Loss (MW)		17.60	5.94	5.39

For the case study 2, the total power demand was increased by 50 %. All the ED results found via MOEP and MOAIS were tabulated in Table 5. While total generation cost and total system loss were reduced to a lower amount using MOAIS and MOEP from non-optimised power system. MOEP continued to provide lower amount of the both objectives than MOAIS. The results also show that the value of PDT was the same for both methods and the non-optimised power system, meaning that all of the constraints were followed properly. MOEP produced total generation cost of 1394.70 $/h and total system loss of 19.27 MW. While MOAIS produced total generation cost of 1396.50 $/h and total system loss of 1396.50 MW and.

Table 5: Comparison of ED Results for 50% Load Increment

Method		Non-Optimised	MOAIS	MOEP
Generator Real Power Output (MW)	P_{g1}	430.53	267.04	248.92
	P_{g2}	40.00	65.38	79.23
	P_{g5}	0.00	49.69	48.40
	P_{g8}	0.00	19.13	31.28
	P_{g11}	0.00	14.94	15.79
	P_{g13}	0.00	29.65	20.75
	$P_{g(total)}$	470.53	445.84	444.37
	PDT	425.10	425.10	425.10
Total Generation Cost ($/h)		1654.20	1396.50	1394.70
Total Loss (MW)		45.44	20.74	19.27

Finally, the experiment continued by increasing the total power demand by 70 %. Table 6 displays all the results of ED of the IEEE 30-Bus RTS taken from non-optimised power system, MOAIS and MOEP. For this case study, the reduction of total generation cost and total system loss obtained via MOEP were lower than those obtained via AIS. Table 6 also shows that the generators' real power output was distributed accordingly with respect to all constraints. Again, the lowest values of the both objectives were found via MOEP. The total generation cost and total system loss obtained via MOEP were 27002.20 $/h and 1.63 MW and respectively. There were significant difference between MOEP and MOAIS especially for the total system loss

Table 6: Comparison of ED Results for 70% Load Increment

Method		Non-Optimied	MOAIS	MOEP
Generator Real Power Output (MW)	P_{g1}	503.40	335.93	307.08
	P_{g2}	40.00	63.52	68.87
	P_{g5}	0.00	49.98	46.42
	P_{g8}	0.00	32.21	32.99
	P_{g11}	0.00	14.66	28.02
	P_{g13}	0.00	16.12	25.40
	$P_{g(total)}$	543.40	512.44	508.78
	PDT	481.78	481.78	481.78
Total Generation Cost ($/h)		2.0551	1.69	1.63
Total Loss (MW)		61.6230	30658.60	27002.20

5. CONCLUSION

Overall, it can be concluded with confidence that the domination of MOEP over the MOAIS method was demonstrated conclusively in the results for all of the cases simulated in this study. Trade-off solutions were found for all cases using WSM. Based on the results, for all case studies, the values of the objectives: total generation cost and total system loss found via MOEP were lower than MOAIS. Furthermore, MOEP clearly did not have any problem in providing lower values in both objectives than MOAIS by optimally distributing the generation between the generators. Therefore, confidently advances that MOEP should be considered the superior method for solving any future ED problem.

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