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Multiverse optimisation based technique for solving economic dispatch in power system

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ABSTRACT

Economic dispatch (ED) is one of the many important components in a power system operation. It is designed to calculate the exact amount of power generation needed to ensure a minimum cost of generation. A power system with multiple generators should be running under an economic condition. The operating cost has to be minimised for any feasible load demand. The increase of power demand is getting higher throughout the year. Economic dispatch is used to schedule and control all output of the fossil-fuel or coal-generators to satisfy the system load demand at a minimum cost. This paper presents the Multiverse Optimisation (MVO) for solving the economic dispatch in a power system. The proposed Multiverse optimisation engine developed in this study is implemented on the IEEE 30-Bus Reliability Test System (RTS). It has five generators, all of which are denoted as the control variables for the optimisation process. To reveal the superiority of MVO, a similar process was conducted using Evolutionary Programming (EP). Results from both techniques were compared, and it was revealed that MVO had outperformed EP in terms of reduced cost of generation for the system.

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1. INTRODUCTION

Generation of power in a utility always aims for minimum cost of generation; this is termed as Economic Dispatch (ED). ED requires optimisation process, where these optimisation techniques have been in existence for a very long time and can be integrated into the ED system. Previously, many engineers have been utilising the calculative methods to solve ED problems, such as Lambda Iteration and Lagrange Multipliers techniques [1]. In the modern era, engineers and researchers have taken interest in Artificial Intelligence (AI), including that of Genetic Algorithm (GA) technique [2], Particle Swarm Optimisation (PSO) [3], and Firefly Algorithm [4], all of which can be used in many different conditions to obtain better and more appropriate results. However, the issues with these methods are that they are not very accurate and can behave speculatively while taking a longer time to compute, as well as producing random population that will generate the local minimum or maximum value.

Traditional analytics-based strategies neglect to address these types of issues accordingly. In contrast to a portion of the customary calculations, Dynamic Programming (DP) [5] forces no confinements on the idea of bending cost. Consequently, it is often adopted to curb the ED issues with innately nonlinear and intermittent cost bends. This strategy experiences the "scourge of dimensionality" or neighborhood optimality issue.

2. LITERATURE REVIEW

2.1. Economic dispatch

Economic dispatch is a generation distribution issue and is characterised as the way toward ascertaining the age unit with the goal that the framework of burden provided is most economical, as per the general inclination requirements. Generally, ED has been adopted since 1920. It was when engineers were stressed over the issue of money related to the dispatching power from generation to consumers. And how to find the most economical division of plant load between the dispatchable generators.

M. Mahmoodi, et al. [6] represented the ED problem with fuel cost, emission, and system failure objectives as a nonlinear multi-objective problem. The future approach of MODE takes an external elitist archive to maintain an algorithm for environmental/economic power transmission non-dominated in Multi-Objective Differential Evaluation (MODE).

Z. Li, et al. [7] have developed an algorithm for units with non-smooth fuel cost functions based on Evolutionary Programming (EP) for general ED. The newly developed algorithm is capable of determining global or near-global optimal dispatch solutions. The results show that the proposed EP-based ED algorithm can provide accurate shipper solutions for all types of fuel cost functions within an appropriate time frame.

Engineers still continue searching for the best answer to spare the activity expenses of intensity ages. Generators must have good productivity level and economic. The goal of comprehending the ED issue is to have control over the yield output of the generators so as to limit the total out-of-pocket cost while supporting the heap power request and different requirements. The ED objective for optimal load dispatch is to reduce the fuel cost of thermal generators while satisfying some of the limits. The function is given by:

$$C = \sum_{i=1}^{NG} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \tag{1}$$

where, a_i, b_i, and c_i are the fuel-cost coefficients; and P_{gi} is the power output for the i^{th} generator among the total committed generators. The overall fuel cost has to be reduced through the following constraints:

2.1.1. Energy balance constraint

The overall generation by all generators should be equal to the sum of whole power demand, P_d and the system's real power loss, P_L.

$$\sum_{i=1}^{NG} P_{gi} - P_d = P_L \tag{2}$$

The power loss is calculated by using B coefficients and unit power output:

$$P_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00} \tag{3}$$

2.1.2. Operatimg limits constraint

The dispatchable generators must be ensured operating within the allowable limits in order to avoid instability in their operation.

2.2. Evolutionary progamming

EP was first developed by Fogel and family, where it was proposed to be used for the advancement of limited state machines to illuminate expected undertakings [8]. From that point onwards, alterations, improvement, and executions have been proposed and explored. The processes of original EP are as shown in Figure 1. EP has been utilised to treat genuine esteemed item factors or some other plausible information structures. Change is frequently actualised by including an arbitrary number or a vector from a specific dispersion [e.g., a Gaussian adaptation on the account of old-style EP (CEP)] to a parent. The variety level of the Gaussian transformation is constrained by its standard deviation, which is otherwise called a methodology parameter in developmental inquiry [9-11]. In the self-adjustment plan of EP, this parameter is not prefixed. It is assumed to have been developed alongside the goal factors. Analyses with self-versatile EP have demonstrated proficient intermingling to quality arrangements [12, 13].

2.3. Multiverse optimisation (MVO)

The MVO technique was first proposed by Seyedali Mirjalili [14-16]. It was invented to simulate the behaviour of white holes, worm holes, and black holes. These holes are as shown in Figure 2. A white hole did not actually exist in the universe, but some astronomical scientists have assumed that the Big Bang can act as a white hole that resulted in the Big Bang occurrence. In a multiverse theory, it is assumed that the parallels had collided with one another when the big bang transpired. A black hole that has the opposite role of a white hole had absorbed all of the objects and planets around them with their force of gravity [17-19]. Wormholes are holes that are interconnected with the different corners of a universe. In the multiverse theory, wormholes act as a time or space travel path, where objects are able to move instantly from one part to any other part of a universe [20-23].

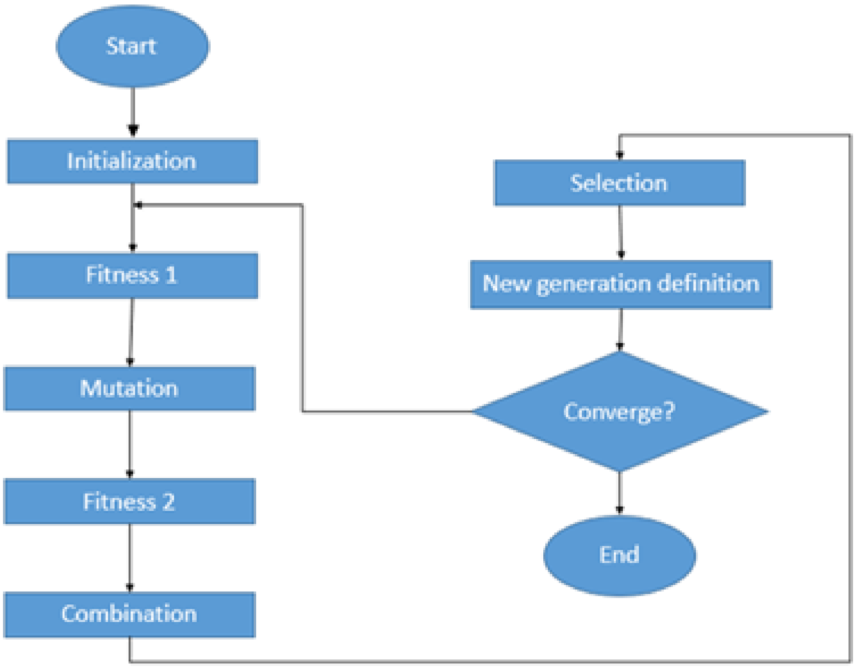

Figure 1. Evolutionary programming algorithm

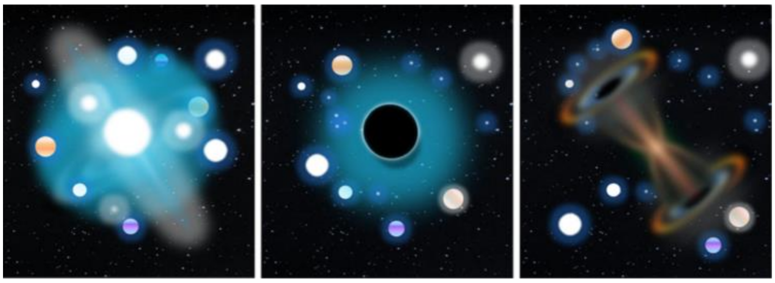

Figure 2. Image of white hole, black hole and worm hole [14]

As previously mentioned, a populace-based calculation separates the pursuit procedure into two stages: investigation versus abuse. The researcher had adopted the idea of white opening and dark gap so as to investigate the search space through the exploitation of MVO. Conversely, the wormholes helped MVO in abusing the inquiry spaces. It is expected that every arrangement is similar to a universe and every factor in the arrangement is an article in that universe. In addition, each arrangement had been allocated a swelling rate, which is relative to comparing the wellness work estimation of the arrangement. Moreover, the term “time” was utilised in this paper rather than the term “cycle”, since it is a typical term in multi-stanza hypothesis and cosmology [24-26]. During the optimisation process, the rules to be applied towards the universe of the MVO are:

a) Increase of inflation rate will increase the probability of a white hole occurrence;
b) Increase of inflation rate will decrease the probability of a black hole occurrence;
c) Universe with a higher inflation rate will tend to send objects through the white hole;
d) Universe with a lower inflation rate will tend to send objects through the black hole; and
e) All objects in all of the universes may face a random movement towards the best universe that it would fit through the wormhole regardless the inflation rate.

Two main coefficients for MVO are:
1. Wormhole Existence Probability

$$WEP = min + l \times \left(\frac{max - min}{L}\right) \tag{4}$$

2. Traveling Distance Rate

$$TDR = \left(1 - \frac{l^{\frac{1}{p}}}{L^{\frac{1}{p}}}\right) \tag{5}$$

MVO algorithm simulates the concept of the universe setting up the number of universes that are desirable, comprising data functions and number of maximum iterations. MVO algorithm is illustrated in Figure 3. MVO will produce the universe inflation, sort it, and normalise the data. This will automatically update the position of each universe and calculate the value of WEP and TDR of every universe. The Roulette Wheel Selection (RWS) algorithm is used to create white holes as indices, depending on the WEP and TDR values. Subsequently, the optimisation engine will update the convergence curve and create the convergence graph.

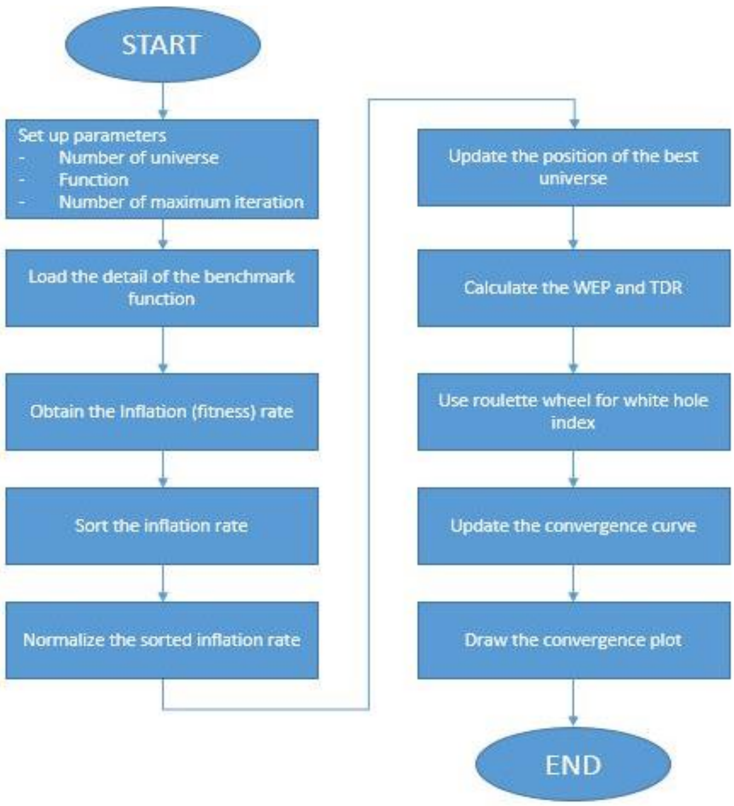

Figure 3. MVO processes

3. RESULTS AND DISCUSSION

In this paper, the MVO and EP were used to determine the optimal generation of the IEEE 30-Bus RTS. The ED program was developed in MATLAB(R2018a), where the population size and the maximum number of iteration were 60 and 500, respectively.

3.1. Case 1

The first case is the generators had run to cater 100 % of power demand (PD), which is 800 MW. Table 1 shows the ED result via MVO: the power generation of each generator, as well as their power losses and total generation cost. From the table above-mentioned, the power generated by Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6 are 32.61 MW, 14.48 MW, 141.56 MW, 136.04 MW, 257.59 MW, and 243.06 MW, respectively. These are the values to achieve the total generation cost of 41896.63 $/h. On the other hand, Table 2 demonstrates the ED result via EP. It shows that the power generated by Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6 at MVO values of 28.06 MW, 17.65 MW, 157.60 MW, 150.62 MW, 241.08 MW, and 229.70 MW, respectively. These values also serve to achieve the total generation cost of 43620.88 $/h. Apparently, with the implementation of MVO, the total generation cost worth 41896.63 $/h can be minimised, as compared to that using EP, which can only minimise it to 43620.88 $/h. This shows that there was a 3.95 % cost reduction by using MVO compared to using EP.

Table 1. ED result via MVO for PD = 800 MW

Unit	Value
Gen 1 (MW)	32.61
Gen 2 (MW)	14.48
Gen 3 (MW)	141.56
Gen 4 (MW)	136.04
Gen 5 (MW)	257.59
Gen 6 (MW)	243.06
Power Loss (MW)	25.33
Total Generation Cost ($/h)	41896.63

Table 2. ED result via EP for PD = 800 MW

Unit	Value
Gen 1 (MW)	28.06
Gen 2 (MW)	17.65
Gen 3 (MW)	157.60
Gen 4 (MW)	150.62
Gen 5 (MW)	241.08
Gen 6 (MW)	229.70
Power Loss (MW)	24.70
Total Generation Cost ($/h)	43620.88

3.2. Case 2

The second case is when the PD was 600 MW, operating 75 % of the maximum power demand. The result of ED via MVO: generators output, power loss, and total generation cost are shown in Table 3. In this table, values of 23.91 MW, 10, 95.54 MW, 100.84 MW, 202.80 MW, and 181.15 MW were obtained for the power generated by Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6, respectively. These are the values for achieving 32094.68 $/h of the total cost of generation. On the other hand, Table 4 of ED results via EP portrays values of 20.70 MW, 10.00 MW, 110.65 MW, 112.23 MW, 188.00 MW, and 172.31 MW for the power generated by Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6, respectively. This resulted in a total generation cost of 33066.35 $/h. Consequently, there can be a minimum reduction in the total generation cost of 32094.68 $/h by implementing MVO, in comparison to EP which only succeeded in minimising the numbers to 33066.35 $/h. This shows that the cost of using MVO is 2.94 % lower than that using EP.

Table 3. ED result via MVO for PD = 600 MW

Unit	Value
Gen 1 (MW)	23.91
Gen 2 (MW)	10.00
Gen 3 (MW)	95.54
Gen 4 (MW)	100.84
Gen 5 (MW)	202.80
Gen 6 (MW)	181.15
Power Loss (MW)	14.24
Total Generation Cost ($/h)	32094.68

Table 4. ED result via EP for PD = 600 MW

Unit	Value
Gen 1 (MW)	20.70
Gen 2 (MW)	10.00
Gen 3 (MW)	110.65
Gen 4 (MW)	112.23
Gen 5 (MW)	188.00
Gen 6 (MW)	172.31
Power Loss (MW)	13.88
Total Generation Cost ($/h)	33066.35

3.3. Case 3

The third case is when the PD was 400 MW. Table 5 shows the ED result via MVO of power loss and total generation cost per generator output. This table includes the power generated from Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6, which had values of 14.84 MW, 10.47.92 MW, 63.77 MW, 144.89 MW, and 125.00 MW, respectively. These are the values to achieve a total generation cost of 22952.83 $/h. While Table 6 of ED result via EP shows the power generated by Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, and Gen 6 were 12.66 MW, 10.02 MW, 58.54 MW, 69.92 MW, 130.10 MW, and 125.00 MW, respectively. This resulted in a total generation cost of 23400.84 $/h. As a result, the total generation cost was reduced to a minimum of 22952.83 $/h through the implementation of MVO, in comparison to the EP which only succeeded in minimising it to 23400.84 $/h. This show that the total generation cost produced using MVO is 1.91 % lower than that using ED.

Table 5. ED result via MVO for PD = 400

Unit	MVO
Gen 1 (MW)	14.83
Gen 2 (MW)	10.00
Gen 3 (MW)	47.92
Gen 4 (MW)	63.77
Gen 5 (MW)	144.89
Gen 6 (MW)	125.00
Power Loss (MW)	6.41
Total Generation Cost ($/h)	22592.83

Table 6. ED result via EP for PD = 400

Unit	MVO
Gen 1 (MW)	12.66
Gen 2 (MW)	10.02
Gen 3 (MW)	58.54
Gen 4 (MW)	69.92
Gen 5 (MW)	130.10
Gen 6 (MW)	125.00
Power Loss (MW)	6.24
Total Generation Cost ($/h)	23400.84

4. CONCLUSIONS

The MVO technique is programmed to imitate the behaviour of white holes, black holes, and worm holes by creating the best universe out of all the variables. This work proposes the Multiverse Optimisation for solving the economic power dispatch (ED) problem in comparison to utilising the Evolutionary Programming. The test was conducted in three different cases, which are 100% power demand, 75% power demand and 50% power demand.

Out of all three cases in the above, the adoption of MVO technique has proven to be more reliable and superior than that using EP in solving ED problems, where all of the results taken from the MVO showed that the total generation cost is lower than the results taken from EP, thus achieving the main objectives of this research. For future studies, MVO can be utilised to solve similar problems in a power system, which may require minor modifications on the developed optimisation engine.

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