Solution to economic load dispatch using quasi-oppositional based CoDE by considering transmission line losses

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Abstract: The main objective of economic dispatch problem is to optimally allocate the load demand among the generating stations such that there is decrease in production cost of the power generation. In the present paper, a quasi-oppositional based composite differential evolution (QOCoDE) technique is proposed to economic load dispatch (ELD) problem. The suggested method provides optimal solutions by combining various strategies in generating trial vector with suitable control parameter settings. The proposed technique is applied on various generating units by considering fixed boundary conditions and transmission losses. The obtained results are compared with various evolutionary algorithms. The results demonstrate the capability of QOCoDE to provide optimal solutions when compared to other evolutionary techniques.

Keywords: - Economic load dispatch, differential evolution, evolutionary algorithm, fixed boundary constraints.

1. Introduction

In power system operation, ELD problem is one of the most vital constrained optimization problems that distribute the load among the generating units such that the power is generated economically. This ELD problem is highly complex and non-linear input–output characteristics and carries out to allocate power by satisfying various inequality and equality constraints. In literature various conventional techniques such as dynamic programming, lambda iteration technique, and gradient technique has been suggested [1], [2]. However, these conventional techniques are sensitive to initial conditions and frequently converge to local optima [3]. Further, these techniques have an oscillatory response in obtaining solution to solve large scale systems. So as to overcome these shortcomings evolutionary methods have been suggested to solve ED problem in literature.

In [4], an enhanced Hopfield neural network (HNN) technique is suggested to enhance the performance of conventional HNN to solve economic load dispatch problem (ELDP). An artificial bee colony (ABC) technique is proposed by incorporating nonlinearities in cost function to solve ELDP in...
In [6], probability selection ABC (PS-ABC) is presented to solve ELDP by considering various constraints such as transmission losses. The proposed algorithm overcomes the premature convergence of standard ABC technique in obtaining optimum solution by introducing two modifications. The first is by improving the mutation equations and the other is by enhancing the scout bee phase in ABC technique. A pattern search (PS) algorithm is suggested by considering transmission losses, valve point effects, cubic cost functions, multi-area, and environmental dispatch to solve ELDP in [7]. In [8], a particle swarm optimization (PSO) is suggested to solve ELDP. However, this method has slow convergence rate and fall into local optima for high dimensional problems. In [9], [10], a biogeography-based optimization (BBO) technique has been suggested to solve ELDP. The authors in [11] has extended the work suggested in [9] by introducing the concept of oppositional based learning to BBO to enhance the convergence speed of conventional BBO. In [12], the performances of PSO is enhanced by incorporating new features such as bi-population and shake mechanism to solve ELDP problem by considering valve point effects and prohibited operating zones (POZs). In [13], a mutative scale chaos optimization algorithm is presented to solve ELDP by considering the design variables interval of the scale to enhance the process of optimization.

In [14], modified harmonic search algorithm (HSO) (MSHO) is suggested to solve ELDP by hybridizing HSO with PSO. Here the process of HSO is improved by utilizing the velocity based particle updating procedure of PSO algorithm. This process has improved the convergence of the MSHO technique. In [15], the authors extended the ELDP to dynamic ELDP by taking into account of predicted load demand over certain interval of time. This approach is solved using simulated annealing technique to obtain global optimum solution by considering spinning reserve constraint. In [16], an improved exponentially harmony search technique is discussed to improve the performance of standard HS technique to solve static ELDP by considering valve point effect. An enhanced fast evolutionary program technique is discussed by taking into account of consumer load patterns in [17]. Similar to [14], the authors in [1] improved the performance of standard PSO by hybridizing it with conventional ACO to form hybrid PSO-ACO to solve ELDP. The performance of this hybrid technique is verified by applying it to 6-generator unit thermal system by considering various constraints transmission losses, ramp rate limits, and prohibited operating zones. In [18], a multi-objective ELDP is solved by considering both cost and emission dispatch. This multi-objective problem is converted to single objective using weighting methodology. To overcome the disadvantages of conventional genetic algorithm (GA) a directional search GA is suggested to solve ELDP in [2]. In [19], memetic algorithm is developed to solve ELDP. In [20], a modified bat algorithm that enhances the performance of bat algorithm by integrating non-inertia weight and hybridized mutation operation. The efficiency of the technique is tested on 3-unit, 13-unit, and 40-unit test systems. In [3], chaotic electromagnetism like mechanism algorithm (EMA) (CEMA) is operated to solve ELDP by incorporating the chaotic dynamics into conventional EMA. This process helped the EMA to avoid getting trapped into local minima. Further research on ELDP can be found in [21]–[23]. From the above literature it has been observed that researchers have applied various evolutionary techniques to solve ELDP by either improving the conventional evolutionary techniques or applying the new technique to obtain minimum cost. However, it can be observed that the performance of these techniques is highly influenced by control parameters to obtain optimum solution. In order to overcome this drawback a quasi-oppositional based composite differential evolution (QOCoDE) is proposed to solve ELDP. To validate the efficiency, the proposed method is applied on 3-unit, 18-unit, and 40 unit test systems both by considering without and with transmission losses. The rest of the paper is organized as follows: ELDP problem formulation is discussed in Section 2. Solution methodology is explicated in Section 3. Results and discussion is elucidated in Section 4. Finally, conclusion is drawn in Section 5.

2. Economic load dispatch problem formulation
Economic load dispatch problem is expressed as a linear optimization problem where the objective is to reduce the total fuel cost production while satisfying the power demand and generator operating
constraints of the generating units [1], [6]. For instance, the generation cost $F$ of an $n$ generating unit system need to be minimized while supplying the load demand $P_D$ of a given power system. This can be expressed mathematically as follows:

$$\min \, F = \sum_{i=1}^{n} C_i(P_i)$$

$$\sum_{i=1}^{n} P_i = P_D$$

(1)

Where, $C_i(P_i)$ is the cost incurred by the $i^{th}$ unit in generating power $P_i$ and $n$ represents the number of generating units.

The smooth fuel cost function can be represented as a quadratic polynomial of generated power which is given below.

$$\sum_{i=1}^{n} C_i(P_i) = \sum_{i=1}^{n} a_i + b_i P_i + c_i P_i^2$$

(2)

Where, $a_i$, $b_i$, and $c_i$ represent the cost coefficients of the $i^{th}$ unit.

Further, the total generated power should not only consider supplying required load demand but also the transmission line losses (TLLs) associated with it [1], [6]. In this case the power balance equation is expressed as

$$\left(\sum_{i=1}^{n} P_i\right) - P_D - P_L = 0$$

(3)

Where, $P_L$ denotes the total TLLs.

These losses are generally calculated using power flow analysis or using Kron’s loss coefficients shown below.

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

(4)

Where, $B_{ij}$, $B_{0i}$, and $B_{00}$ represent the loss $B –$ coefficients of the given power system network, $B_{ij}$ is the loss coefficient $ij^{th}$ element of the symmetric matrix $B$, $B_{0i}$ is the loss coefficient vector of $i^{th}$ element, and $B_{00}$ is the loss coefficient constant.

Further, the generated power by each unit should satisfy the maximum $P_{\text{max}}$ and minimum $P_{\text{min}}$ limits of each generating unit.

$$P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}}, \text{ for } i = 1, 2, 3, \ldots, n.$$  

(5)

The equations (2) to (5) makes the ELDP as simplified approximate problem and the characteristic cost curve is considered to be piecewise linear function.

3. Solution methodology using quasi-oppositional based composite differential evolution algorithm

Alike all evolutionary techniques, the initial population of QOCoDE of size $NP$ is randomly generated by sampling across the feasible search space in the following way [24].

$$z_i = \{z_{i,1}, z_{i,2}, \ldots, z_{i,\phi}\}, \quad i = 1, 2, \ldots, NP$$

(6)
Each individual of the parent population is called target vector. Now, for each target vector of the current population another vector known as mutant vector \( v_i = \{v_{i,1}, v_{i,2}, \ldots, v_{i,n}\} \) is obtained by performing difference vector mutation using 3 dissimilar trial vector generation strategies and 3 control parameter settings to form the candidate approach and the parameter pools, respectively [24]. The following candidate parameter pool is considered in the present work.

1. \([F = 1, CR = 0.1]\);
2. \([F = 1, CR = 0.9]\);
3. \([F = 0.8, CR = 0.2]\);

Further, the following three candidate strategies are considered to perform difference vector mutation vectors [24]. Then, binomial crossover process is accomplished between mutant vector and target vector to obtain a trial vector \( u_i \).

1. "\(rand/1/bin\)"
   \[
   u_{i,j} = \begin{cases} 
   z_{i,j} + F.(z_{i,j} - z_{r,j}), & \text{if } \text{rand} < CR \text{ or } j = j_{\text{rand}} \\
   z_{i,j} & \text{otherwise} 
   \end{cases}
   \]  
   \( (7) \)

2. "\(rand/2/bin\)"
   \[
   u_{i,j} = \begin{cases} 
   z_{1,j} + F.(z_{2,j} - z_{r,j}) + F.(z_{4,j} - z_{5,j}), & \text{if } \text{rand} < CR \text{ or } j = j_{\text{rand}} \\
   z_{i,j} & \text{otherwise} 
   \end{cases}
   \]  
   \( (8) \)

3. "\(current-to-rand/1\)"
   \[
   u_{i,j} = z_i + \text{rand}.(z_{1,i} - z_j) + F.(z_{2j} - z_{r,j})
   \]  
   \( (9) \)

It is to be noted here that binomial crossover is not performed on third mutation strategy.

After obtaining the three trial vectors for each mutation vector, the best fittest trial vector is selected. Now after obtaining \( NP \) trial vectors, selection operation is performed between trial vector and target vector [24]. The best among trial vector and target vector is selected using equation as shown in \( (10) \). This process repeats until the stopping criteria have been achieved.

\[
\hat{z}_i = \begin{cases} 
    u_i & \text{if } f(u_i) \leq f(z_i) \\
    z_i & \text{otherwise} 
\end{cases}
\]  
\( (10) \)

After performing selection operation, quasi-opposition based learning (QOBL) concept is applied on each individual of the population. To perform QOBL, opposite vector to the present vector and mean of the search space are required to be calculated [25]-[30]. Here, the opposite vector to the given vector and the mean of the search space are calculated in the following way.

If \( z_j(z_{j1}, z_{j2}, \ldots, z_{jd}) \) is a vector comprising of \( d \)-real numbers whose upper and lower limits are \( z_j = [z_{j1}^{\text{min}}, z_{j1}^{\text{max}}] \) \( \forall j \in \{1, 2, \ldots, d\} \) then its opposite vector \( oz_j(oz_{j1}, oz_{j2}, \ldots, oz_{jd}) \) is obtained using \( (11) \).

\[
oz_j = z_{j1}^{\text{max}} + z_{j1}^{\text{max}} - z_j
\]  
\( (11) \)
The mean \((m_z)\) of the search space limit is calculated as:

\[
m_z = \frac{z_{\min} + z_{\max}}{2}
\]  

Mathematically, the QOBL is obtained using (13)

\[
QOZ_j = \text{rand} \left( \frac{z_{j\min} + z_{j\max}}{2} \right) + z_{j\min} - z_j
\]  

Now, each vector after performing selection operation is compared with the \(QOZ\) vector obtained above to select the best individual for next generation or iteration.

4. Results and discussion

The proposed QOCoDE methodology to solve ELDP has been programmed in MATLAB 8.1a. The efficiency and reliability to attain optimal solution has been tested on four test systems, namely 3 units, 18 units, 20 units, and 40 units. Further, two case studies namely ELDP with and without transmission losses has been considered. The results thus obtained using the proposed QOCoDE method is compared with directional search genetic algorithm (DSGA) and Hopfield Neural network (HNN) proposed in the literature.

4.1. Case Study 1: Without Transmission loss

Test Case 1: The optimum generated power for unit 3 system against two different load demands, i.e. 1080 MW and 1140 MW has shown in Table 1. The cost coefficients \((a, b, c)\) and the B-Loss coefficients are taken from [2]. Table 1 consists of five columns. Column 1 represents the unit number, Columns 2 and 3 represent the optimum power generated using the proposed QOCoDE and DSGA for 1080 MW load demand, and Columns 4 and 5 represent the optimum power generated using the proposed QOCoDE and DSGA for 1140 MW load demand. From the results it is observed that the suggested method provides better results when compared to DSGA for all the load demands. For example, for load demand of 1140 MW the total cost obtained using the proposed QOCoDE is 10915.16 \$/hr which is less than the total cost obtained using the DSGA, i.e. 10915.41 \$/hr. This shows the efficiency of the proposed method to obtain optimum power generation.

| Unit | Load | DSGA [2] | Proposed QOCoDE | DSGA [2] | Proposed QOCoDE |
|------|------|---------|-----------------|---------|-----------------|
|      | 1080 (MW) | 1140 (MW) |
| 1    | 517.4950 | 517.4867 | 562.8100 | 562.8016 |
| 2    | 399.9890 | 162.5133 | 399.9800 | 177.1984 |
| 3    | 162.5156 | 400 | 177.2000 | 400 |
| TC (\$/hr) | 10338.7700 | 10338.7165 | 10915.4100 | 10915.1611 |

Test Case 2: The optimum generated power for unit 18 system against three different load demands, i.e. 346.576 MW, 368.237 MW, and 411.559 MW has shown in Table 2. The cost coefficients \((a, b, c)\) and the B-Loss coefficients are taken from [2]. Table 2 consists of seven columns. Column 1 represents the unit number, Columns 2 and 3 represent the optimum power generated using the proposed QOCoDE and DSGA for 346.576 MW load demand, Columns 4 and 5 represent the optimum power generated using the proposed QOCoDE and DSGA for 368.237 MW load demand, and Columns 6 and 7 represent the optimum power generated using the proposed QOCoDE and
DSGA for 411.559 MW load demand. From the results it is observed that the suggested method provides better results when compared to DSGA for all the load demands. For example, for load demand of 411.559 MW the total cost obtained using the proposed QOCoDE is 29729.2511 $/hr which is less than the total cost obtained using the DSGA, i.e. 29731.39 $/hr. Further, from Table 3 it can also observe that the proposed method provides less total generation cost compared to both GA and DSGA. This shows the efficiency of the proposed method to obtain optimum power generation.

| Unit | Load | DSGA [2] | Proposed QOCoDE | DSGA [2] | Proposed QOCoDE | DSGA [2] | Proposed QOCoDE |
|------|------|----------|-----------------|----------|-----------------|----------|-----------------|
| 1    | 15   | 45       | 45              | 45       | 45              | 45       | 45              |
| 2    | 25   | 25       | 25              | 25       | 25              | 25       | 25              |
| 3    | 25   | 25       | 25              | 25       | 25              | 25       | 25              |
| 4    | 25   | 25       | 25              | 25       | 25              | 25       | 25              |
| 5    | 25   | 25       | 25              | 25       | 25              | 25       | 25              |
| 6    | 3    | 4.6600   | 4.6688          | 13.7000  | 13.7033         |
| 7    | 3    | 4.6600   | 4.6678          | 13.7000  | 13.7114         |
| 8    | 12.2800 | 12.2800   | 12.2800         | 12.2800  | 12.2800         |
| 9    | 12.2800 | 12.2800   | 12.2800         | 12.2800  | 12.2800         |
| 10   | 12.2800 | 12.2800   | 12.2800         | 12.2800  | 12.2800         |
| 11   | 12.2800 | 12.2800   | 12.2800         | 12.2800  | 12.2800         |
| 12   | 20.7200 | 20.7228   | 23.2400         | 23.2454  | 24              |
| 13   | 3    | 3        | 6.4120          | 6.4141   |
| 14   | 30.8600 | 30.8701   | 35.0500         | 35.0564  | 36.2000         |
| 15   | 32.3600 | 32.3654   | 36.2900         | 36.2966  | 45              |
| 16   | 33.2400 | 33.2484   | 37              | 37       | 37              |
| 17   | 33.2400 | 33.2492   | 37.1800         | 37.1820  | 45              |
| 18   | 3    | 3        | 6.4120          | 6.4102   |
| TC ($/hr) | 23855.2700 | 23853.4709   | 25710.4400   | 25708.8234 | 29731.3900 | 29729.2511 |

Table 3. Comparison of optimal power generation cost for unit 18 system with 346.576 MW

| Methods | GA [2] | DSGA [2] | Proposed QOCoDE |
|---------|--------|----------|-----------------|
| Total Generation Cost ($/hr) | 23857.54 | 23855.27 | 23853.4709 |

Test Case 3: The optimum generated power for unit 40 system against load demand of 9500 MW has shown in Table 4. The cost coefficients \((a, b, c)\) and the B-Loss coefficients are taken from [2]. Table 4 consists of three columns. Column 1 represents the unit number, Columns 2 and 3 represent the optimum power generated using the proposed QOCoDE and DSGA for 9500 MW load demand. From the results it is observed that the suggested method provides better results when compared to DSGA for all the load demands. For example, for load demand of 9500 MW the total cost obtained using the proposed QOCoDE is 107247.6947 $/hr which is less than the total cost obtained using the DSGA, i.e. 128424.26 $/hr. Further, the obtained results are also compared with HNN and classical method in Table 5. From this table it can be seen that the proposed QOCoDE offers better results. This shows the efficiency of the proposed method to obtain optimum power generation.
**Table 4. Comparison of optimal power generation levels for unit 40 system**

| Unit | Load | Optimal Power Generation (MW) |
|------|------|------------------------------|
|      |      | **DSGA [2]** | **Proposed QOCoDE** |
| 1    | 80   | 125            |                       |
| 2    | 120  | 114            |                       |
| 3    | 190  | 113.9999       |                       |
| 4    | 42   | 89.7922        |                       |
| 5    | 42   | 134.3822       |                       |
| 6    | 140  | 97             |                       |
| 7    | 300  | 116.2345       |                       |
| 8    | 300  | 299.9999       |                       |
| 9    | 300  | 299.9999       |                       |
| 10   | 152.4940 | 300           |                       |
| 11   | 171.5710 | 130           |                       |
| 12   | 171.9840 | 94            |                       |
| 13   | 267.4800 | 94            |                       |
| 14   | 393.0840 | 125.0063      |                       |
| 15   | 395.1750 | 125.0005      |                       |
| 16   | 395.1750 | 125.0012      |                       |
| 17   | 395.1750 | 437.2447      |                       |
| 18   | 500  | 440.2112       |                       |
| 19   | 500  | 437.6536       |                       |
| 20   | 550  | 437.1760       |                       |
| 21   | 550  | 549.9999       |                       |
| 22   | 550  | 549.9999       |                       |
| 23   | 550  | 549.9999       |                       |
| 24   | 550  | 550            |                       |
| 25   | 550  | 549.9997       |                       |
| 26   | 550  | 549.9999       |                       |
| 27   | 550  | 549.9999       |                       |
| 28   | 10.9520 | 10            |                       |
| 29   | 10.9520 | 10            |                       |
| 30   | 10.9520 | 97            |                       |
| 31   | 20   | 190            |                       |
| 32   | 20   | 190            |                       |
| 33   | 20   | 190            |                       |
| 34   | 20   | 199.9999       |                       |
| 35   | 18   | 200            |                       |
| 36   | 18   | 200            |                       |
| 37   | 20   | 110            |                       |
| 38   | 25   | 110            |                       |
| 39   | 25   | 110            |                       |
| 40   | 25   | 437.2988       |                       |

| TC ($/hr) | 128424.3000 | 107247.6947 |
Table 5. Comparison of optimal power generation cost for unit 40 system

| No of Units | Load (MW) | DSGA [2] | Classical Method [9] | Hopfield Neural Network [9] | Proposed QOCDE |
|-------------|-----------|----------|----------------------|-----------------------------|----------------|
| 40          | 9500      | 128.4    | 128.4                | 129.1                       | 107.247        |

4.2. Case Study 2: With Transmission loss

The optimum generated power for unit 20 system against load demand of 2500 MW has shown in Table 6. The cost coefficients \((a_i, b_i, c_i)\) and the B-Loss coefficients are taken from [4]. Table 6 consists of four columns. Column 1 represents the unit number, Columns 2, 3 and 4 represent the optimum power generated using the NR, HNN, and proposed QOCODE for 2500 MW load demand. From the results it is observed that the suggested method provides better results when compared to NR and HNN. For example, for load demand of 2500 MW the total cost obtained using the proposed QOCODE is 62,451.5987 $/hr which is less than the total cost obtained using the NR and HNN, i.e. 62,489.5 $/hr and 62,610 $/hr, respectively. Further, it can be observed that total losses obtained using the proposed QOCODE is less when compared to other methods. This shows the reliability of the proposed method to obtain optimum power generation.

Table 6. Comparison of optimal power generation levels for unit 20 system

| Unit | Method         | Newton-Raphson [9] | HNN [9] | Proposed QOCODE |
|------|----------------|---------------------|---------|-----------------|
| 1    | 524.0166       | 403.3043            | 512.2680 |
| 2    | 160.9879       | 134.4348            | 169.0413 |
| 3    | 130.2168       | 134.4348            | 126.5931 |
| 4    | 100.4129       | 134.4348            | 102.5626 |
| 5    | 115.2559       | 107.5478            | 113.6593 |
| 6    | 78.7385        | 67.2174             | 73.0546  |
| 7    | 118.1765       | 84.0217             | 114.7470 |
| 8    | 18.939         | 100.8261            | 116.2247 |
| 9    | 104.7037       | 134.4348            | 100.5933 |
| 10   | 113.7706       | 100.8261            | 105.7405 |
| 11   | 148.7055       | 201.6522            | 150.3420 |
| 12   | 295.9623       | 336.0869            | 292.0552 |
| 13   | 118.02         | 107.5478            | 120.8808 |
| 14   | 35.4054        | 87.3826             | 30.8607  |
| 15   | 121.372        | 124.3522            | 115.6681 |
| 16   | 36.0465        | 53.7739             | 36.8531  |
| 17   | 72.453         | 57.1348             | 67.9272  |
| 18   | 42.2129        | 80.6609             | 87.8393  |
| 19   | 102.6087       | 80.6609             | 100.6815 |
| 20   | 55.756         | 67.2174             | 54.1207  |
| TL   | 93.7615        | 97.952              | 91.7132  |
| TC ($/hr) | 62489.5 | 62610 | 62451.5987 |

5. Conclusions

In the present work, QOCODE has been applied to solve the ELDP by considering various test systems and case studies. The proposed method provides optimal solutions by combining three different mutation vector strategies in generating trial vector along with three different scaling factor and
crossover rate control parameter settings. It has been observed from the results that the proposed method has effectively optimizes power generation that should be scheduled across different generators. It is shown that the proposed QOCoDE method is quite cost-effective and transmission loss saving when compared to GA, DSGA, NR, and HNN algorithms. In future, various operating constraints such as valve point loading, prohibited operating zones, and ramp rate limits will be considered.

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