Artificial Neural Network Based on Optimal Operation of Economic Load Dispatch in Power System

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ABSTRACT:

The LaGrange iterative method was construct to solve the problem of power losses reduction case to minimize the total fuel cost generation. It difficult to optimize nonlinearity cost functions of fuel generators in power systems with equality and inequality constraints. This paper presents an approach method of optimization for solving the economic load dispatch (ELD) problem with generator constraints and satisfying the load demand irrespective of transmission line losses. To verify the proposed work, an artificial neural network (ANN) based Lambda iterative optimization method with Matlab R2018a program is being apply to the test system. The numerical studies have been accomplished to IEEE model system (30-bus 6-generator, 41-line and 20-load). The results have manifests the effectiveness of the supposed algorithms because it can provide accurate dispatch solutions with wide range of load demand in minimum total cost. Further analyses indicate the total power losses in the system.

KEY WORDS: ANN; Economic load dispatch; Power system stability; Quadratic cost function; and Lambda iterative method.
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1. INTRODUCTION:

The economic load dispatch (ELD) problem seeks the best generation schedule for the generating plants to supply the required demand plus transmission losses with the minimum production cost. Conventionally, the emphasis on performance optimization of fossil–fuel power systems was on economic operation only, using the ELD approach, as better solutions would result in significant economic benefits (Zhihang et al., 2013). The total electrical energy losses of transmission line have a negative effect on environment; also decrease the overall efficiency of the systems.

Conversely, in local high voltage or low voltage distribution networks to satisfy the load demand distributed energy resources composed of distributed generations and energy storage devices are incorporated (Gomez et al., 2014). Optimal economic dispatch problems in electrical power systems should be solve minimization operation of the total fuel costs by setting the output power of each generator so as satisfy the load demand and related operational constraints. Since 1920, many experts and researchers conducted in the field of energy engineering related research. Optimal theories and circuits are base of economic dispatch problem. The power flow algorithm applied on real-time system states to compute the all bus voltages and line flows of power systems. However solutions computing by those methods are accurate, but more iterations and time-consuming processes to convergence problem (Acha and Kazemtabrizi, 2013; Chai et al., 2015; Kim, 2016; Raygani et al, 2012). Open
literature describe many computer programs of power system during the last three decades, (Neyer et al., 1990). Several of these software’s were designing to provide a variety of engineering analysis ranging from load flow to transient stability. Others have been developed to plan and control the power system in real-time (Foley and Bose, 1995).

The network sensitivity factor methods, like as shift distribution factor generation (Soman et al., 2015), and Jacobian-based distribution factor (JBDF) (Huang and Yao, 2012), have been suggested so as to progress the computation of speed running programs and reduce of iterations. The applied of this access overcomes the impairment of Newton Raphson and Gauss-based load flow algorithms in economic dispatch. General optimum algorithms in economic dispatch and unit commitment are based on non-linear Lagrange multiplier methods (Sun et al., 2015) and meta-heuristic approaches (Marlon and Osvaldo, 2013). Soroudi and Rabiee approached a new model to solve the problem of dynamic multiple-zone ED by studying uncertainties in wind power generation, energy fuel costs and power system demands. Optimal state analysis is also used to verify the proposed approach to real-time operation of process power systems (Soroudi and Rabiee, 2013).

This paper study the optimal economic dispatch in electrical power system based on artificial neural network optimization technique program by using Matlab software program and find total power losses and total cost generations.

2. PROBLEM FORMULATION

The standard of optimal power flow problem can be written as:

Minimization of the objective function F(x)

which subject to equality constraints \{ g_i(x) = 0 \}

and inequality constraints \{ a \leq h_i(x) \leq b \}

The major factor play an effective role of the optimum dispatch of generation is power transmission loss. The transmission line loss PL formula of ED load problem consider as below.

Minimize of objective function:

\[
C_{total} = C_1 + C_2 + C_3 + \cdots + C_{ng} \text{ \$/hr} \quad (1)
\]

where \( C_i = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \) \quad (2)

\( C_i \) is the incremental fuel cost for the \( i^{th} \) generating unit; and \( \alpha_i, \beta_i \) and \( \gamma_i \) represents fuel constant coefficients.

Subject to

\[
P_{i\min} \leq P_i \leq P_{i\max} \quad (3)
\]

Here, \( P_{i\min} \) and \( P_{i\max} \) represent lower and higher power generation limits for the \( i^{th} \) generating unit

\[
\sum_{i=1}^{ng} P_i = P_D + P_L \quad (4)
\]

Here, \( P_D \) is power system demand and \( P_L \) is transmission power losses.

Transmission power loss is considered to be quadratic function, which is given as:

\[
P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{j=1}^{ng} B_{0j} P_j + B_{00} \quad (5)
\]

Here, \( B_{ij} \), \( B_{0j} \), and \( B_{00} \) are loss constant coefficients of systems.

The generalized objective function \( C_{total} \) is a non-linear function, increasing of the generation bus of power systems leads to increase the number of the equality and inequality constraints. Applications of an optimization technique such as the Lambda Iterative algorithm by using Matlab program are very suitable to solve the problem of a large power distribution system with a more non-linear objective functions and great number of constraints.
3. TRAINING THE NETWORK BY ANN

Artificial Neural Networks are made up of large interconnected neural numerating elements of a parallel distributed network processing. These networks have the ability to learn and store the acknowledgements. These acknowledgements make neural network to solve any problems (Aree, 2018). The learning of ANN may be either supervised or unsupervised. During the training the actual outputs for each input signal are made availability to the network (Tarik and Nian, 2016). The aim of ED is to minimizing the generation cost rate simultaneously at appropriate interval while satisfying various constraints. The constrained optimization can be modified as:

\[ C_T = \sum_{k=1}^{T} \sum_{i=1}^{n_g} [\alpha_i + \beta_i P_i^k + \gamma_i (P_i^k)^2] \]  

The interconnection between the artificial neurons in an Artificial Neural Network (ANN) gave it the flexibility to adapt and copy any mathematical model (Eisa, 2013). In the last decades, it’s been found that the nonlinear relationship between the inputs and the outputs in any black-box system can be replaced with ANN. This modeling is depicted as a supervised training procedure. This procedure gives the ability of the network’s interconnections to adjust using the error signal in a way that the network output tries to track the desired output. Providing data to the network continues until the error is reduced to a predefined value. Network training was achieved using the method of Levenberg-Marquardt backpropagation (LMBP) due to its fast training process (Tommy and Siu, 2007). This method has the property of approaching to second-order training speed with no computation of the Hessian matrix H.

\[ H = J^T J \]  

where J is the Jacobian matrix that contains first derivatives of the network error with respect to the weights and biases. The LMBP algorithm uses the following approach to minimize the total error e:

\[ x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \]  

The topology of this ANN shows in Fig. 1(a). The hyperbolic tangent (tanh) as an activation function used for the hidden units, the identity function has been used for the output ones.

Once the multilayer perceptron MLP topology is fixed, the ANN learns the relationship between input and output elements. For that, the network must be trained. The target values are a set of patterns training data consisting of input and corresponding output values. For each entire training pattern process, the weights are updated. This updating is done in such a way that a measure of the error in the network’s results is minimised as shown in Fig. 1(b) for this work.
and total transmission line power losses PL by solving equation (5).

Step 3. Apply ANN based Lambda Iterative

Evaluate the fitness function $\Delta \lambda$.

Step 4. Repeat the step 2 and step 3 until the process has been converged or it satisfies the stopping criteria.

Step 5. Limiting Power generation

If optimal power under not maximum and minimum limits, fix that generate power and repeat the step 2, 3 and 4.

Step 6. Find total fuel cost

Step 7. Stop

Fig. 2 shows the Flowchart of economic dispatch using ANN based Lambda iterative technique.

![Flowchart of economic dispatch using ANN based Lambda iterative technique](image)

**Figure 1.** (a) Topology of the multilayer perceptron. (b) Neural Network Training

**Figure 2.** Economic dispatch flowchart using ANN based Lambda iterative technique
5. CASE STUDY

The ANN based Lambda iterative method is a very effective tool for the linear optimization problems that are able to handle both equalities constrained and inequality constrained linear optimization problems. Numerous computational programming methods, such as the barrier method, inner point and the Lambda iterative method have been developed and punished based on the basic rules of the Lambda iterative method. The Lambda iterative method and its extensive methods are widely applied in science, engineering, economics and our daily life.

In addition the optimal total cost of a test system been calculated for a various particular power demand. IEEE 30-bus model system have been employed to carried out various case studies, a proposed approach system with six generating as shown in Fig. 3. units is optimized and simulated by using Intel Core i7-3612QM, 2.10 GHz, 8 GB memory. The proposed algorithm was applied in MATLAB R2018a program.

![Figure 3. Topology of the IEEE 30-bus model system](image)

Table 1 shows the minimum and maximum active power limits of six generators of the proposed system and constant coefficients of the quadratic cost functions. The full algorithm of optimum solution of total fuel cost for a proposed six-unit generating system shown in Fig. 2. Losses coefficient $B$ are given in Table 3.

| Bus Number | $P_{E_i}^{\text{min}}$ [MW] | $P_{E_i}^{\text{max}}$ [MW] | $\alpha$ [$/\text{hr}]$ | $b$ [$$/\text{MWh}$$]$$\times 10^{-4}$ | $c$ [$$/\text{MW}^2\text{hr}$$]$$\times 10^{-4}$ |
|------------|-----------------------------|-----------------------------|----------------------|---------------------------------|---------------------------------|
| Bus 1      | 50                          | 200                         | 0                    | 2.00                            | 37.5                            |
| Bus 2      | 20                          | 80                          | 0                    | 1.75                            | 175.0                           |
| Bus 5      | 15                          | 50                          | 0                    | 1.00                            | 625.0                           |
| Bus 8      | 10                          | 35                          | 0                    | 3.25                            | 83.0                            |
| Bus 11     | 10                          | 30                          | 0                    | 3.00                            | 250.0                           |
| Bus 13     | 12                          | 40                          | 0                    | 3.00                            | 250.0                           |

Table 1: Generators parameters of the IEEE 30-bus Electrical Network
6. SIMULATION RESULTS

The ED program is an effective code in the Matlab environment according to the system model and solving algorithms. The proposed method employed to solve the ED problem of the original system of the IEEE 30-bus model and verify the accuracy and effectiveness of the proposed method, and the relevant parameter of the ED and power flow are obtained. The numerical and ANN results (Table 2) demonstrate all results of the developed ED program. Matlab Software code were using to generate the output power in MW/hr, fuel cost of generators in $/hr and the total operational cost against the multiple power demand in MW. Fig. 4 and Fig. 5 show optimum output power and fuel cost of each six generating unit system with change of power demand respectively. Fig. 6 shows the minimum total cost of the proposed system with and without ANN against change of power demand.

Table 2: The simulation results of the traditional ANN based Lambda Iterative technique method for the ED of the original IEEE 30-bus test system.

| P_D = 320MW | P_D ≤ 260MW | P_D ≥ 380 MW |
|-------------|-------------|-------------|
|             | in case P_D = 250 MW | In case P_D = 400 MW |
| P_1 actual  | 188.6354 MW | 155.533 MW | P_1 (Fixed) actual 200.00 MW |
| P_1 ANN     | 188.6362 MW | 155.5307 MW | P_1 (Fixed) ANN 200.00 MW |
| P_2 actual  | 51.4141 MW | 43.3428 MW | P_2 actual 79.891 MW |
| P_2 ANN     | 51.4149 MW | 43.3417 MW | P_2 ANN 79.905 MW |
| P_5 actual  | 21.9275 MW | 19.005 MW | P_5 actual 39.378 MW |
| P_5 ANN     | 21.9282 MW | 19.0046 MW | P_5 ANN 39.389 MW |
| P_8 actual  | 29.5766 MW | 11.662 MW | P_8 (Fixed) actual 35.00 MW |
| P_8 ANN     | 29.5779 MW | 11.6595 MW | P_8 (Fixed) ANN 35.00 MW |
| P_11 actual | 14.8047 MW | 10.00 MW | P_11 (Fixed) actual 24.601 MW |
| P_11 ANN    | 14.8055 MW | 10.00 MW | P_11 (Fixed) ANN 24.615 MW |
| P_13 actual | 13.719 MW | 12.00 MW | P_13 (Fixed) actual 21.234 MW |
| P_13 ANN    | 13.7195 MW | 12.00 MW | P_13 (Fixed) ANN 21.244 MW |
| P_L actual  | 0.169 MW | 0.1298 MW | P_L actual 0.2495 MW |
| P_L ANN     | 0.163 MW | 0.103 MW | P_L ANN 0.241 MW |
| C_total actual | 898.1143 $/hr | 663.2001 $/hr | C_total actual 1225.9 $/hr |
| C_total ANN | 885.47 $/hr | 652.51 $/hr | C_total ANN 1210.7 $/hr |
Figure 4. Relationship between all optimal output powers with power demand

Figure 5. Relationship between all minimum costs of generators with power demand
Figure 6. Relationship between minimum total costs of the system with and without ANN against power demand

7. CONCLUSIONS

The focus of this economic dispatch paper is to analysis power systems so as to get the optimal economic utility while reducing cost. The cost reduction process makes the system more efficient. The modeling and simulation process was also used to demonstrate the effectiveness of using Artificial Neural Network by Matlab software as a tool for quick, clear, accurate and explicit decision when planning the economic dispatch process as an engineering system.

This paper also focused on power demand, when power demands less than 265MW output power of at generator-11 and generator-13 should fix at minimum and for power demand greater than 350MW output power of at generator-1 and generator-8 should fix at maximum. The total cost reduce 12.6643 $/hr at 320MW power demand and also reduce to 15.2 $/hr at 400MW power demand.

Table 3: Generalized loss coefficients data for IEEE-30 bus system

\[
B_0 = \begin{bmatrix}
0.000218 & 0.000103 & 0.000009 & -0.000010 & 0.000002 & 0.000027 \\
0.000103 & 0.000181 & 0.000004 & -0.000015 & 0.000002 & 0.000030 \\
0.000009 & 0.000004 & 0.000417 & -0.000131 & -0.000153 & -0.000107 \\
-0.000010 & -0.000015 & -0.000131 & 0.000021 & 0.000094 & 0.000050 \\
0.000002 & 0.000002 & -0.000153 & 0.000094 & 0.000243 & -0.000000 \\
0.000027 & 0.000030 & 0.000107 & -0.000050 & -0.000000 & 0.000358
\end{bmatrix}
\]

\[
B_{90} = [-0.000003 \quad 0.000021 \quad -0.000056 \quad 0.000034 \quad 0.000015 \quad 0.000078]
\]

\[
B_{90} = [0.000014]
\]
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