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A Deep Neural Network Approach for Optimizing Economic Load Dispatch in Power Systems

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ABSTRACT: To ensure minimization of power losses as well as economic feasibility of electrical power generation, economic load dispatch happens to be one of the most challenging optimization problems which is faced in electrical engineering. With the advent of distributed power systems, an interconnection of power systems generating from different sources have come into consideration. However, all sources do not operate in the same manner and hence the generation cost for different sources varies significantly. Economic Load Dispatch (ELD) can be defined as a technique to schedule the power generator outputs with respect to the load demands, and to operate the power system in the most economical way. This paper presents a neural network model for implementing economic load dispatch for a three as well as six generation system. The load is also varied for both the 3 and 6 generations systems. The results clearly indicate that the cost of generation increases with the increase in load, which is also intuitive and hence gets tested. Thus the proposed model can be used to implement an optimized economic load dispatch mechanism for multi-unit power systems which is a typical characteristic of distributed power systems.
Keywords: Power Systems, Loss Minimization, Economic Load Dispatch, Optimization Techniques, Neural Networks.

I. INTRODUCTION:

Loss minimization and economic load dispatch (ELD) are two critical aspects of power system operation, particularly in interconnected systems. In an interconnected power system, multiple power generation units, often located in different regions, work together to meet the electricity demand [1]. The goal of these systems is to supply power efficiently, reliably, and at the lowest possible cost while minimizing transmission losses. Achieving optimal economic load dispatch and loss minimization ensures that electricity is delivered sustainably and economically.Power losses in transmission lines are an inevitable part of power delivery due to the resistance and reactance of conductors. In large interconnected systems, these losses can be significant, reducing overall efficiency [2].

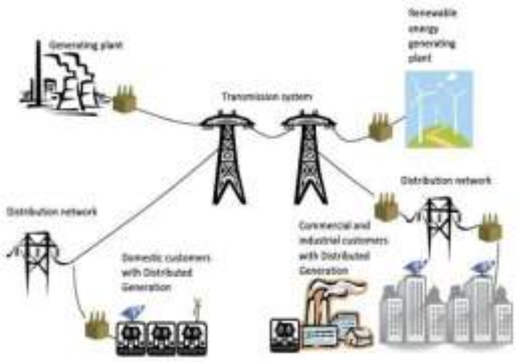

Fig.1 An interconnected power system

Figure 1 depicts and interconnected power system, wherein multiple sources can be connected to a grid to contributed energy.Loss minimization aims to reduce these losses, which are typically categorized into two types: real power losses (I^2R losses) and reactive power losses. Various methods, such as reactive power compensation, optimal power flow (OPF) algorithms, and network reconfiguration, can be employed to minimize losses [3]. Reducing transmission losses not only improves system efficiency but also supports the objectives of economic load dispatch, as fewer losses translate into lower generation costs [4].

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II. LOSS MINIMIZATION AND ECONOMIC LOAD DISPATCH

In an interconnected power system, the ELD problem becomes more complex due to the multiple areas involved. Each area may have its own generation units, constraints, and load demands. Interconnections between areas allow for the sharing of resources, which can lead to cost savings. Power can be transferred from regions with surplus generation to regions with deficits, thereby optimizing the overall system operation [5]. However, this necessitates coordination among the areas to achieve both economic efficiency and reliability. Advanced computational techniques, such as linear programming, dynamic programming, and heuristic methods, are commonly used to solve the ELD problem in interconnected systems [6].

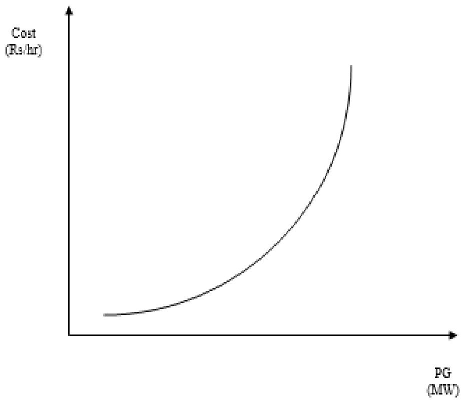

Fig.2 Typical variation of cost of generation with generation magnitude

Figure 2 depicts the typical variation of cost of generation with generation magnitude interconnected power systems face several challenges in achieving loss minimization and economic load dispatch. These challenges include variations in fuel costs, fluctuating demand patterns, transmission constraints, and the need for real-time adjustments due to unforeseen outages or failures. Moreover, with the growing integration of renewable energy sources, which are intermittent and less predictable, the complexity of managing the economic dispatch process increases. Effective coordination between different regions, along with accurate forecasting and advanced control techniques, is essential to address these challenges [7].

By optimizing power generation and reducing transmission losses, utilities can ensure a reliable supply of electricity at the lowest possible cost. With the use of advanced optimization techniques and a focus on real-time system control, interconnected power systems can better handle the growing complexity and dynamic nature of modern electricity grids, contributing to both economic efficiency and environmental sustainability [8].

III. MATHEMATICAL FORMULATION FOR LOSS MINIMIZATION AND ELD:

This section presents the mathematical model for optimized loss minimization. Consider n generators in the same plant or close enough electrically so that the line losses may be neglected [9]. Let C_1, C_2, …, C_n be the operating costs of individual units for the corresponding power outputs P_1, P_2,.,P_n respectively. If C is the total operating cost of the entire system and P_R is the total power received by the plant bus and transferred to the load.Consider the objective function [10]:

$$\mathbf{C = \sum_{i=1}^{n} C_i\left(P_{G_i}\right)} \quad \textbf{(1)}$$

One needs to minimize the above function subject to the equality and inequality constraints.

Equality constraints: The real-power balance equation, i.e., total real-power generations minus the total losses should be equal to real-power demand [11]:

$$\mathbf{P_{G_i} - P_L = P_D} \quad \textbf{(2)}$$

Here,

P_{G_i} denotes power generated by generation unit ‘i’.

P_D denotes dispatched power.

Inequality constraints:The inequality constraints are represented as:

1. In terms of real-power generation as
$P_{Gi\,(min)} \leq P_{Gi} \leq P_{Gi(max)}$

2. In terms of reactive-power generation as
$Q_{Gi\,(min)} \leq Q_{Gi} \leq Q_{Gi(max)}$

3. In addition, the voltage at each of the stations should be maintained within certain limits.
i.e., $V_{i(min)} \leq V_i \leq V_{i(max)}$

Current distribution factor of a transmission line w.r.t a power source is the ratio of the current it would carry to the current that the source would carry when all other sources are rendered inactive i.e., the sources that do not supply any current.

If the system has ‘n’ number of stations, supplying the total load through transmission lines, the transmission line loss is given by [12]:

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$$\mathbf{P_L = \sum_{p=1}^{n}\sum_{q=1}^{n} P_{Gp}B_{pq}P_{Gq}} \qquad (3)$$

The coefficient **B**are called loss coefficients or B-coefficients and are expressed in $(MW)^{-1}$. The transmission loss is expressed as a function of real-power generations.
The incremental transmission loss is expressed as $\frac{\partial P_L}{\partial G}$[13].
The penalty factor of any unit is defined as the ratio of a small change in power at that unit to the small change in received power when only that unit supplies this small change in received power and is expressed as [14]:

$$L_i = \frac{1}{1-\frac{\partial P_L}{\partial P_{G_i}}}$$

The condition for optimality when transmission losses are considered is

$$\frac{\partial C_1}{\partial P_{G_1}}L_1 = \frac{\partial C_2}{\partial P_{G_2}}L_2 = \cdots = \frac{\partial C_n}{\partial P_{G_n}}L_n = \lambda$$

To optimize the cost function, several approaches have been employed thus far.

IV. THE NEURAL NETWORK MODEL FOR OPTIMIZATION

Several methods are employed for both loss minimization and ELD. Classical methods like the Newton-Raphson method, gradient-based techniques, and linear programming have been widely used. However, with the growing complexity of power systems and the need for more precise solutions, modern optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), and artificial neural networks (ANNs) are now being utilized. These methods can handle non-linearities, constraints, and uncertainties more effectively, offering better results in terms of cost savings and loss reduction. The neural network model (with deep neural networks) has proven to be one of the most effective optimization techniques off late. This is the primary reason why the neural network model has been chosen in this research workThe unit wise generation is modelled as follows [15]:

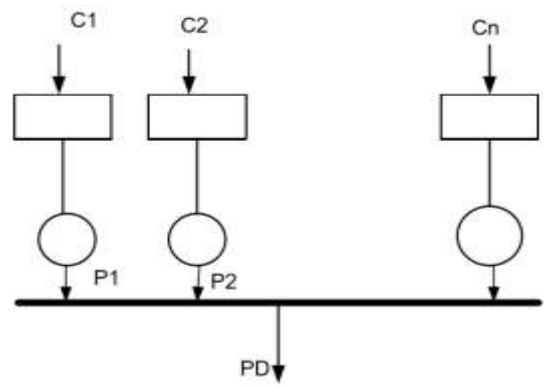

Fig.3. Model for Power Generation System with Multiple Sources

Considering the total cost of generation to be the sum of individual costs of generations of the generators, we get [16]:

$$\mathbf{GC_{tot} = \sum_{i=1}^{n} k_1 P_{gi}^{m} + k_2 P_{gi}^{m-1} + \cdots . + k_m} \mathbf{(4)}$$

Here,
k1, k2….. km are the constants
P_{gi} is the individual power generated by a generator
GC_{tot} is the total cost of generation
The aim of employing the neural network is to minimize the cost function by optimizing the generation of each generator [17]:
The output of the neural network is given by:

$$\mathbf{y = f(\sum_{i=1}^{n} XiWi + \Theta)} \qquad \mathbf{(5)}$$

Where,
Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and
ϴ is the bias. It can be seen that various signals traverssing different paths have been assigned names X and each path has been assigned a weight W. The signal traverssing a particular path gets multiplied by a corresponding weight W and finally the overall summation of the signals multiplied by the corresponding path weights reaches the neuron which reacts to it according to the bias ϴ. Finally its the bias that decides the activation function that is responsiblefor the decision taken upon by the neuralnetwork. The activation function φ is used to decide upona the final output. The neural network model is presented next [18]:

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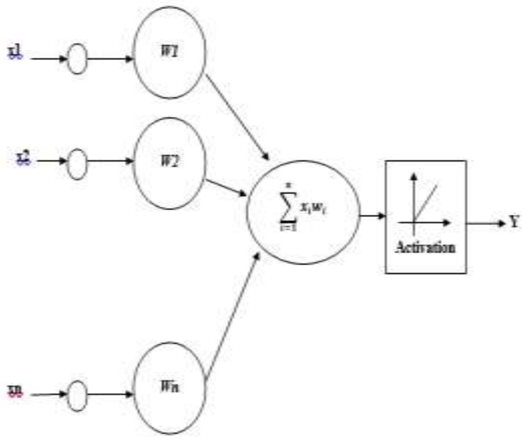

Fig.4 Mathematical Model of Neural Network

The learning capability of the ANN structure is based on the temporal learning capability governed by the relation:

$$\mathbf{w(i) = f(i, e)} \quad \mathbf{(6)}$$

Here,
w (i) represents the instantaneous weights
i is the iteration
e is the prediction error

The weight changes dynamically and is given by:

$$\mathbf{W_k \xrightarrow{e,i} W_{k+1}} \quad \mathbf{(7)}$$

Here,
W_k is the weight of the current iteration.
W_{k+1} is the weight of the subsequent iteration.

(i) Regression Learning Model

Regression learning has found several applications in supervized learning algorithms where the regression analysis among dependednt and independent variables is eeded. Different regression models differ based on the the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used. Regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a relationship between x (input) and y(output). Mathematically,

$$\mathbf{y = \theta_1 + \theta_2 x} \quad \mathbf{(8)}$$

Here,
x represenst the state vector of inut variables
y rperesenst the state vector of output variable or variables.
ϴ1 and ϴ2 are the co-efficents which try to fit the regression learning models output vector to the input vector.

By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ1 and θ2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y). The cost function J is mathematically defined as [19]:

$$\mathbf{J = \frac{1}{n}\sum_{i=1}^{n}(pred_1 - y_i)^2} \quad \mathbf{(9)}$$

Here,
n is the number of samples
y is the target
pred is the actual output.

(ii) Gradient Descent

To update θ1 and θ2 values in order to reduce Cost function (minimizing MSE value) and achieving the best fit line the model uses Gradient Descent. The idea is to start with random θ1 and θ2 values and then iteratively updating the values, reaching minimum cost. The main aim is to minimize the cost function J.The critical aspect about steepest descent is the fact that it repeatedly feeds the errors in every iteration to the network till the errors become constant or the maximum number of allowable iterations are over. This can be mathematically given by:

if $PF \neq$ constant
for $(k = 1, k \leq k_{max} = \text{constant}, k = k + 1)$
{
$$W_{k+1} = f(X_k, W_k, e_k)$$
}
else
{
$W_{k+1} = W_k$ && training stops
}

Here,
X_k is the input to the kth iteration
W_k is the weight to the kth iteration
W_{k+1} is the weight to the (k+1)st iteration
e_k is the error to the kth iteration
k is the iteration number
PF is the performance function deciding the end of training
k_{max} is the maximum number of iterations

Thus if the error is within tolerance, which is generally not feasible to find beforehand in time series data, the training is stopped if the performance function (which can be the training error) becomes constant for multiple iterations or the maximum number of iterations are over. Now there are various ways in which the error can be

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minimized. However, the steepest fall of the error with respect to weights is envisaged. It is depicted in the figure below:

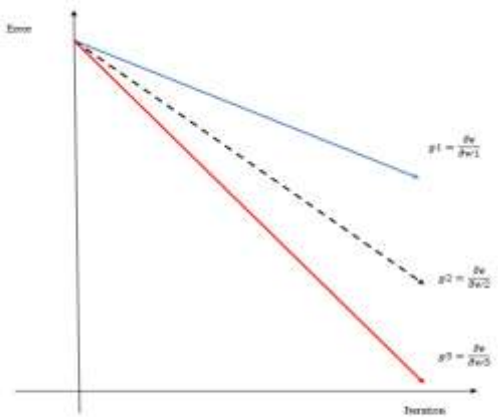

Fig.5. The concept of Steepest Descent

It can be seen from figure 5 that although the error in training keeps plummeting in all the three cases of gradient descent, the gradient 3 or g3 attains the maximum negative descent resulting in the quickest training among all the approaches and hence the least time complexity. This would be inferred from the number of iterations which are required to stop training. Thus the number of iterations would be a function of the gradient with which the error falls.

This is mathematically given by:

$$\mathbf{k_n = f(g = \frac{\partial e}{\partial w})(10)}$$

Here,

k_n is the number of iterations to stop training.

g is the gradient

w is the weight

e is the error

f stands for a function of

The proposed methodology uses two key components one of which is the training algorithm and the other is the training optimization algorithm. The weight update can give represented as:

$$\mathbf{w_{k+1} = w_k - \mu_k \frac{\partial e}{\partial w_k}(11)}$$

Here,

w_{k+1} is the weight of the next iteration

w_k is the weight of the present iteration

μ_k is the combination co-efficient

IV. EXPERIMENTAL RESULTS

The experimental results are simulated on MATLAB. Both 3 and 6 unit systems have been simulated for variable load scenarios.

The upper bounds for the 3 unit system are considered as:

$$20 < P1 < 150$$
$$20 < P2 < 150$$
$$20 < P3 < 150$$

The upper bounds for the 6 unit system are considered as:

$$30 < P1 < 200$$
$$45 < P2 < 250$$
$$30 < P3 < 200$$
$$40 < P4 < 200$$
$$45 < P5 < 250$$
$$40 < P6 < 200$$

The neural network model is simulated next:

Fig.6. Training of Neural Network Model

Figure 6 depicts the training function for the neural network model.

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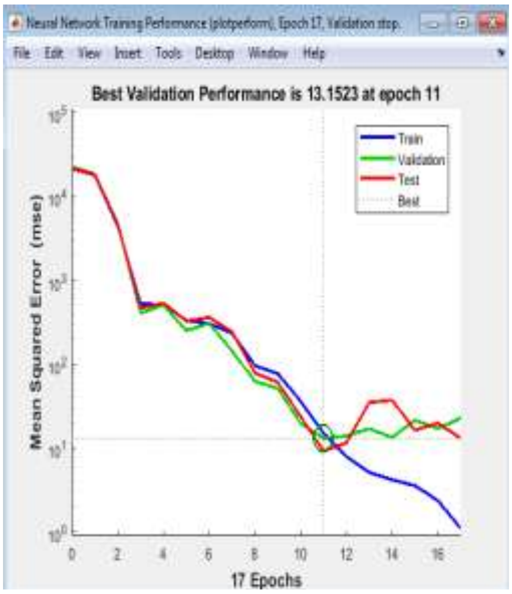

Fig.7. Training Convergence

Figure 7 depicts the training convergence of the model.

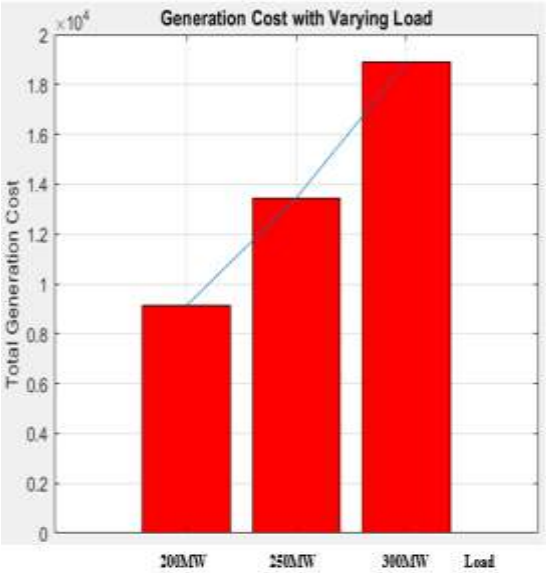

Fig.8. Variation in Cost of Generation (3 unit system)

Figure 8 depicts the variation in cost of generation of 3 unit system.

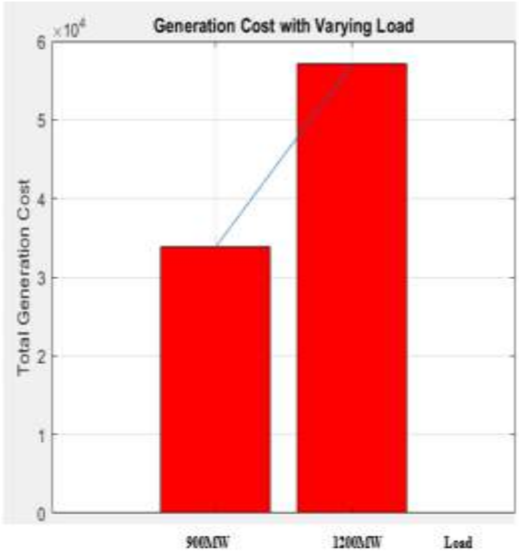

Fig.9. Variation in Cost of Generation (6 unit system)

Figure 9 depicts the variation in cost of generation for 6 unit system.

It can observed that the cost of generation increases with generational capacity magnitude. By learning the relationships between these variables, a neural network can suggest optimal configurations that reduce real power losses. Additionally, neural networks can be integrated into optimal power flow (OPF) algorithms, which aim to minimize both losses and generation costs simultaneously, by adjusting generation levels and power flows across the network.

CONCLUSION:

This paper presents aneural network approach for implement the economic load dispatch for a multi unit system.The major advantage of using neural networks for ELD and loss minimization is their ability to handle non-linearity and uncertainties. Power systems are inherently non-linear due to the varying nature of loads, transmission line characteristics, and generation units. Neural networks, being non-linear models, can capture these complexities more accurately than traditional linear or gradient-based methods. Additionally, neural networks can be retrained with new data to adapt to changing conditions, making them highly flexible. This makes them suitable for real-time applications, where system conditions change dynamically, requiring fast and accurate decision-making.Two cases of 3 and 6 unit systems have been simulated with specified upper and lower bounds and it can be observed that the neural network model attains

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fast convergence and low mean squared error value of 13.15 at convergence at 17 iterations.

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