Emission Constrained Economic Dispatch using Radial Basis Function Neural Network

P. S. Kulkarni, A. G. Kothari and D. P. Kothari

Abstract— The aim of the paper is to compare the performance of Radial Basis Function Neural Network (RBFNN) with Backpropagation Neural Network (BPNN) with respect to solution optimality, execution time and memory for the solution of Emission Constrained Economic Dispatch (ECED) problem. Focus is on Nitrogen Oxide (NO\textsubscript{x}) as its control is a significant issue at the global level. The equality constraint of power balance, inequality thermal generator capacity and emission constraints are included. The total load (MW) supplied is the input to the neural network. The thermal generator outputs and total system transmission losses are considered as outputs of the neural network. Results predicted by RBFNN have been compared with the existing Quick Method (QM) and it is observed that RBFNN results satisfy inequality generator capacity and emission constraints at various load levels and transmission losses are also nearly the same as the Quick Method. RBFNN shows simple architecture, better accuracy, speed and requires less computer memory compared to BPNN. Validity and effectiveness of the proposed RBFNN technique has been demonstrated by analyzing a sample system.

Index Terms-- emission constrained economic dispatch, radial basis function neural network, sum squared error.

I. INTRODUCTION

Electric power systems and their operation are among the most complex problems in today’s civilisation due to highly non-linear and computationally difficult environments. The basic requirement of Economic Dispatch (ED) is to generate adequate electricity to meet continuously changing customer load demand at the lowest possible cost under a number of constraints [1]. Due to stringent governmental regulations on environmental protection, the conventional operation at absolute minimum fuel cost cannot be the sole basis for dispatching electric power. Society needs quality and reliable power at the cheapest possible price with minimum acceptable levels of pollution. Since the passage of U.S. Clean Air Act Amendments 1990 and similar Acts by European and Japanese Governments, environmental constraints have topped the list of utility management concerns [2]. Therefore, it is mandatory for electric utilities to reduce pollution level by reducing CO, CO\textsubscript{2}, SO\textsubscript{2} and NO\textsubscript{x}.

Several methods available for reducing emissions are: i) switching to fuels with low emission potential, ii) installing post-combustion cleaning system and iii) allocation of generation to each generator unit with the objective of minimum emission dispatch. All these means are expensive and need to be complemented by the implementation of an Environmental Constrained Economic Dispatch (ECED) which is a relatively low cost method to reduce emission without violating the constraints.

Many researchers have included emissions either in the objective function or treated them as constraints. Several methods have been proposed [3]-[5] since the early work by Gent and Lamont [6]. Recently, modern heuristic techniques such as Artificial Neural Networks, Fuzzy Logic, Simulated Annealing and Evolutionary Programming have been applied to solve this problem.

Like many other engineering disciplines, neural networks are finding increasing application in several aspects of power system control. Neural networks are highly simplified models of the human nervous systems, exhibiting abilities such as Learning, Generalization and Abstraction. Neural networks learn from experience and their characteristics make them suitable for solving practical problems accurately and quickly, even in the presence of incomplete information. In this paper, a Radial Basis Function Neural Network (RBFNN) has been designed, trained and tested for the solution of Emission Constrained Economic Dispatch problem. As an illustration, only control of nitrogen oxide, (NO\textsubscript{x}) is considered. The equality constraint of power balance, inequality generator capacity and emission constraints are taken into account. The proposed neural network technique has been applied successfully and the results are compared with the Quick Method (QM) [7].

II. PROBLEM DESCRIPTION

Minimum cost scheduling with specified emission limit is normally obtained by the iterative solution technique [8]. Incremental procedures are available [6]. Non-iterative method such as Direct Method [9] may also be used. For a given load condition, different generation schedules are possible without violating the specified emission limit. All of them may not give the minimum operating cost. The problem of choosing a particular schedule which gives the minimum cost dispatch without violating the emission constraints is discussed here. A graph between the value of price penalty factor \( h \) and NO\textsubscript{x} emission is essential for this approach.

The graph is obtained from the system data and the methodology given as in [7] is as under:
i) With the present load, assume different values of \( h; \) say, 0, 10, 20, 30, 40, 50, \ldots \text{etc.} When \( h = 0, \) this is economic dispatch criterion.

ii) For each value of \( h, \) solve for the individual plant generation using the Quick Method, applied by the authors in their earlier work [3]. The required equations are:

\[
\begin{align*}
\min \phi_i &= \sum_{i=1}^{n} \left[ (a_i + h d_i) P_i^2 + (b_i + h e_i) P_i + (c_i + h f_i) \right] \\
&= \ldots \text{Rs} / \text{h} \quad (1)
\end{align*}
\]

\[
\sigma_1 \lambda^2 + \sigma_2 \lambda + \left( \sigma_3 - P_D \right) = 0 \\
\sigma_4 \lambda^2 + \sigma_5 \lambda + \sigma_6 = 0 \quad \ldots (2)
\]

\[
P_i = (\alpha_i \lambda^2 + \beta_i \lambda + \gamma_i) \quad \text{MW} \\
i = 1, 2, \ldots, n \quad (3)
\]

iii) With each generation schedule obtain the \( NO_x \) emission by

\[
E_i = d_i P_i^2 + e_i P_i + f_i \quad \text{kg} / \text{h} \quad i = 1, 2, \ldots, n \quad (4)
\]

iv) For the different assumed values of \( h \) and the evaluated \( NO_x \) emissions, a graph is drawn between them as shown in Fig. 1.

v) This procedure is repeated for all other loads as and when needed.

Let the controlled emission be \( NO_x' \) or the emission should not exceed \( NO_x' \) at optimum dispatch. Corresponding to \( NO_x' \) obtain the value of \( h' \) from Fig. 1. Now \( h' \) is known and the emission constrained economic dispatch problem is defined as follows.

\[
\min \phi_i = \sum_{i=1}^{n} \left( a_i P_i^2 + b_i P_i + c_i \right) + \sum_{i=1}^{n} \left( d_i P_i^2 + e_i P_i + f_i \right) \\
\quad \text{Rs} / \text{h} \quad (5)
\]

where \( h' \) is the price penalty factor corresponding to \( NO_x' \), subject to:

\[
(i) \quad P_{i, \text{min}} \leq P_i \leq P_{i, \text{max}} \quad i = 1, \ldots, n \quad (6)
\]

\[
(ii) \quad \sum_{i=1}^{n} P_i = P_D + P_L \quad (7)
\]

and

\[
(iii) \quad \sum_{i=1}^{n} E_i \leq NO_x' \quad (8)
\]

Though iterations are not needed, various curves \( (h \text{ vs } NO_x') \) are necessary for the different load conditions of the system. The off-line computation time is more, but the on-line solution time and steps are reduced. Delson’s [8] iterative approach has convergence problem and the solution is not guaranteed. There is no convergence problem in the approach suggested by Palanichamy and Srikrishna [7] and the emission constrained economic dispatch is obtained directly. For training BPNN, the approach described by these authors has been applied.

In this paper, the problem of optimizing the system operating cost with \( NO_x \) emission is solved by a quadratic equation in \( \lambda \). The solution technique is simple, reliable and fast. The number of plants does not pose any constraint in the solution strategy. Capacity, demand and emission constraints as specified by regulatory agencies are duly considered. This simple solution technique, with appropriate evaluation of coefficients \( \sigma_1, \sigma_2, \sigma_3, \alpha_i, \beta_i, \gamma_i \) form an efficient algorithm in the fields of economic and environmental dispatch areas.

**Operating Constraints** [7]

Equation (6) gives,

\[
P_{i, \text{min}} \leq P_i \leq P_{i, \text{max}} \\
i = 1, \ldots, n
\]

**Lower generation limit**. At optimum dispatch, if the optimum generation of the \( j^{th} \) generator goes below its lower limit \( P_{j, \text{min}} \), then the \( j^{th} \) generator is allowed to generate power equal to \( P_{j, \text{min}} \). The remaining \( (n - 1) \) generators are allowed to share the power by

![Graph](image-url)
\[ P_D^j = P_D - (P_{j,\text{min}} - P_{j,\text{min}}^2 B_j^1) \]  

(9)

where \( B^1 \) is newly computed diagonal term for various values of \( j \) of the \( B \) matrix.

Upper generation limit: At optimum dispatch, if the optimum generation of the \( j^{th} \) generator goes above its upper limit \( P_{j,\text{max}} \), then the \( j^{th} \) generator is allowed to generate its full capacity \( P_{j,\text{max}} \). The remaining \((n-1)\) generators are allowed to share the power by

\[ P_D^j = P_D - (P_{j,\text{max}} - P_{j,\text{max}}^2 B_j^1) \]  

(10)

III. RADIAL BASIS FUNCTION NEURAL NETWORK

RBFNN shares features of the Backpropagation Neural Network (BPNN) for pattern recognition. It is being extensively used for on- and off-line non-linear adaptive modelling and control applications. RBFNN stores information locally whereas the conventional BPNN stores the information globally. A schematic diagram of a radial basis function (RBF) network with inputs and \( m \) outputs is shown in Fig. 2. The architecture of the RBF network consists of an input layer, a hidden layer and an output layer. The input vector to the network is passed to the hidden layer nodes via unit connection weights. The hidden layer consists of a set of radial basis functions. Representing a bias is optional. Associated with each hidden layer node is a parameter vector \( \mathbf{c} \) called a center. The hidden layer node calculates the Euclidean distance between the center and network input vector and then passes the result to the radial basis function. All the radial basis functions in the hidden layer nodes are usually of the same type. Thus the hidden layer performs a fixed nonlinear transformation with no adjustable parameters and it maps the input space onto a new space. The output layer then implements a linear combiner on this new space and the only adjustable parameters are the weights of this linear combiner. These parameters can be determined using the linear least squares method. In this paper, the centers of the RBF and the weights are found by using the OLS learning algorithm.

IV. SOLUTION ALGORITHM

In neural network approach to emission constrained economic dispatch problem, the following steps are followed in getting near optimal solutions.

- **Step 1**: Identify the inputs and outputs for the problem under consideration and select the neural network architecture.
- **Step 2**: Using an analytical method such as Quick Method, generate the input – output training pairs by varying load demand in step.
- **Step 3**: Normalize the input – output training pairs using a suitable normalization technique.
- **Step 4**: Apply the normalized input – output training pairs to the neural network.
- **Step 5**: Train the neural network using a suitable training algorithm.
- **Step 6**: Get the neural network results by applying few test input patterns (patterns not covered in the training set). Denormalize these results.
- **Step 7**: For test cases, compare the results predicted by neural network with any other existing method.

V. TEST RESULTS

In this paper, the proposed RBFNN approach for ECED has been applied to a test system [7] consisting of six thermal generators.

From Table I it is clear that the results predicted by RBFNN are in close agreement with the QM and BPN results. Further, the results do not violate the individual generator capacity and emission limits.

### TABLE I

<table>
<thead>
<tr>
<th>Met</th>
<th>QM [4]</th>
<th>BPN</th>
<th>RBN</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_1 )</td>
<td>33.36</td>
<td>33.71</td>
<td>32.81</td>
</tr>
<tr>
<td>( P_2 )</td>
<td>24.15</td>
<td>24.67</td>
<td>23.49</td>
</tr>
<tr>
<td>( P_3 )</td>
<td>91.29</td>
<td>87.46</td>
<td>88.24</td>
</tr>
<tr>
<td>( P_4 )</td>
<td>92.26</td>
<td>89.04</td>
<td>89.36</td>
</tr>
<tr>
<td>( P_5 )</td>
<td>138.2</td>
<td>133.2</td>
<td>133.3</td>
</tr>
<tr>
<td>( P_6 )</td>
<td>134.2</td>
<td>128.6</td>
<td>129.6</td>
</tr>
<tr>
<td>( P_L )</td>
<td>11.63</td>
<td>10.88</td>
<td>11.06</td>
</tr>
<tr>
<td>( F_T )</td>
<td>27797.1</td>
<td>27069.9</td>
<td>27061.2</td>
</tr>
<tr>
<td>( E_T )</td>
<td>266.8</td>
<td>254.89</td>
<td>255.18</td>
</tr>
</tbody>
</table>

Met: Method  
QM: Quick Method  
BPN: Back-propagation neural network  
RBN: Radial basis function neural network  
\( P_0 \): Power demand (MW)  
\( P_1 \) – \( P_6 \): Generations (MW)  
\( P_L \): Total System transmission loss (MW)  
\( F_T \): Total generation cost (Rs / h)  
\( E_T \): Total NO\textsubscript{X} emission (kg / h)  

Various specified emission levels are assumed for load variation within 500-1100 MW. Using the QM, 151 input-
output training patterns are generated in this load range keeping a step size of 4 MW. Initial small random weights are assumed. BPN uses $\text{logsig}$ transfer function in hidden and output layers. BPN took 938 epochs during training to reach the error goal (0.02).

The real design decision for RBFNN (besides picking an error goal) is finding a good value for the Spread Constant (SC). RBFNN is designed using the function $\text{solverb}$ and simulated using the function $\text{simurb}$ available with MATLAB NEURAL NETWORK TOOLBOX [10]. Fig. 3 shows that RBFNN requires only 4 hidden layer neurons to reach the same error goal.

![Fig. 3. SSE versus epoch by radial basis function neural network.](image)

Examination of Table II shows that Percentage Error (P.E.) is less in case of RBFNN compared to BPNN.

<table>
<thead>
<tr>
<th>$P_0$</th>
<th>Ass. NOx</th>
<th>PE in $F_T$</th>
<th>PE in $E_T$</th>
</tr>
</thead>
<tbody>
<tr>
<td>502</td>
<td>267</td>
<td>2.61</td>
<td>2.64</td>
</tr>
<tr>
<td>682</td>
<td>425</td>
<td>2.49</td>
<td>2.42</td>
</tr>
<tr>
<td>910</td>
<td>718</td>
<td>2.06</td>
<td>2.20</td>
</tr>
<tr>
<td>1078</td>
<td>1007</td>
<td>2.97</td>
<td>2.18</td>
</tr>
</tbody>
</table>

P.E. $= \frac{\text{QM result - NN result}}{\text{QM result}} \times 100$ (11)

Mean error in $F_T$ is 2.53% by BPNN and 2.36% by RBFNN. Further, mean error in $E_T$ is 4.84% by BPNN and 4.51% by RBFNN.

Table III shows that RBFNN gives saving in computational time and memory.

<table>
<thead>
<tr>
<th>Comp. Time (sec)</th>
<th>Mem. (bytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>QM</td>
<td>BPN [4]</td>
</tr>
<tr>
<td>14763</td>
<td>3839</td>
</tr>
</tbody>
</table>

* On Pentium 166 MHz

VI. CONCLUSION

Environmental concern is an extremely important issue in the operation of modern power systems. This paper focuses on single pollutant NOx, because its control is a significant issue at the global level. For the solution of ECED problem, a RBFNN technique has been proposed. The equality constraint of power balance, inequality generator capacity and emission constraints are considered. Results predicted by a RBFNN are compared with the existing Quick Method with respect to solution optimality, execution time and memory. It is observed that, results predicted by the proposed neural network satisfy inequality generator capacity and emission constraints at various load levels and transmission losses are also nearly the same as the Quick Method. Further, RBFNN shows simple architecture, better accuracy, speed and requires less computer memory compared to BPNN.

VII. REFERENCES