Environmentally Constrained Economic Dispatch Via Neural Networks

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Abstract: Operating at absolute minimum cost can no longer be the only criterion for dispatching electric power due to increasing concern the environmental consideration. The environmentally constrained economic dispatch problem which accounts for minimization of both cost and emission is a multiple objective function problem. In this paper, an improved Hopfield neural network which was described in [1] is applied to environmentally constrained economic dispatch problem. Sample test results are presented.

1. INTRODUCTION

The economic dispatch (ED) is an optimization problem to find the most economical schedule of the generating units while satisfying load demand and operational constraints. This problem has been tackled by many researchers in the past. The literature of the ED problem and its solution methods are surveyed in [2] and [3].

The generation of electricity from fossil fuel releases several contaminants, such as Sulfur Oxides, Nitrogen Oxides and Carbon Dioxide, into the atmosphere. Recently the problem which has attracted much attention is pollution minimization due to the pressing public demand for clean air. Since the text of the Clean Air Act Amendments of 1990 and similar Acts by European and Japanese governments, environmental constraints have topped the list of utility management concerns [4]. A summary of environmental/economic dispatch algorithms dating back to 1970 using conventional optimization methods has been provided [5].

Several methods have been used to represent emission levels. Kermanshahi et al. [6] used the sum of a quadratic and an exponential term. Nandi et al. [7] tried to find the best compromise between the conflicting targets of minimum cost and minimum emission by means of suitable multiobjective procedures. Granelli et al. [8] proposed an emission constrained dynamic dispatch procedure. It minimizes fuel cost during a preselected time horizon and thoroughly takes into account the environmental constraints.

Artificial neural networks (NN) are finding applications in several aspects of power system. Application of artificial neural networks to economic dispatch has become an active research area in recent years. Kumar and Sheble [9] described a method for real-time economic dispatch using Kennedy, Chua and Lin NN. Transmission losses and demand constraints only were taken into account. The Kennedy-Chua NN was justified for linear and quadratic programming problems and the proposed method was applied to the ED problem [10]. Park et al. [11] proposed to apply a Hopfield NN to the economic dispatch problem for a piecewise quadratic cost function. King et al. [12] reported an improved Hopfield NN for the economic-environmental dispatch problem and illustrated 3-unit and 12-unit systems. The Hopfield NN and the Taboo Search technique have been applied to the environmental economic dispatch problem by Rao-Sepulveda et al. [13]. They presented a 3-unit test system to validate the proposed methods.

The environmental economic dispatch problem can be classified as a multiobjective optimization and non-linear programming problem. Standard Hopfield networks [14] have already been applied to different optimization problems. Gee et al. [15,16] discussed a new methodology to improve the performance of Hopfield networks. The authors formalized the mapping process and provided a computational method for obtaining the weights and biases for the Hopfield networks. Gee's method is quicker and more accurate and is thus more efficient than the standard Hopfield neural network method. This new mapping technique has been used for solution of large scale economic dispatch problems by Yalcinoz and Short [1]. The proposed method has achieved efficient and accurate solutions for different sizes of systems having between 3 and 240 units.

In this paper, a method using improved Hopfield neural networks [1] to solve the environmentally constrained economic dispatch problem is proposed. The proposed method is able to solve a multiobjective function. The proposed method minimizes the operation cost while SO_2 and NO_x are reduced.

2. THE PROBLEM FORMULATION

The classic economic dispatch problem aims to supply the required quantity of power at the lowest possible cost [17]. The dispatch problem can be stated mathematically as follows:

To minimize the total fuel cost at thermal plants:

$$F = \underset{P_i}{Min} \sum_{i=1}^{n} (a_i + b_i P_i + c_i P_i^2) \qquad (1)$$

subject to the equality real power balance constraints:

$$\sum_{i=1}^{n} P_i - P^D - P^L = 0 \qquad (2)$$

where

$$P^L = \sum_{i=1}^{n} B_i P_i^2 \qquad (3)$$

the inequality constraint of limits on the generator outputs is:

$$P_{min,i} \le P_i \le P_{max,i} \qquad (4)$$

where a_i, b_i and c_i are the cost coefficients of the i-th generator and n is the number of generators committed to the operating system. P_i is the power output of the i-th generator, P^D is the load demand and P^L represents the transmission losses.

However there is a large financial beneficial from the classical dispatch strategy described above, it tends to produce high SO_2 and NO_x emissions. An alternative dispatch strategy to satisfy the environmental requirement is to minimize operation cost under environmental constraints. Emission control can be included in conventional economic dispatch by adding the environmental cost to the normal dispatch. The emissions need to be converted as an environmental cost and added to the generation cost. The objective function then becomes

$$\text{Minimize } C = w0\, F + w1\, E_S + w2\, E_N \qquad (5)$$

Where E_S is the SO_2 emission function, E_N is the NO_x emission function. W0, w1 and w2 are cost, SO_2 emission and NO_x emission weights respectively.

In this paper, like fuel cost curves, the SO_2 and the NO_x curves can be expressed as follows:

$$E_S = \sum_{i=1}^{n} (d_i + e_i P_i + f_i P_i^2) \qquad (6)$$

and

$$E_N = \sum_{i=1}^{n} (g_i + h_i P_i + k_i P_i^2) \qquad (7)$$

where d_i, e_i, f_i, g_i, h_i and k_i are parameters estimated on the basis of unit emissions test results.

In this model, when emission weights are equal to zero, the objective function becomes a classical economic dispatch problem. In this economic dispatch option, units are to minimize the total system production costs. When cost weight is set to zero, the problem becomes emission minimization. In this case, units are to minimize the amount of emissions. When weights are not zero in the objective function, the problem becomes minimizing the fuel cost plus emission at the same time.

3. HOPFIELD NEURAL NETWORK

The Hopfield model [14] is a single layer recursive neural network where the output of each neuron is connected to the input of every other neuron. The energy function of the Hopfield NN, which is a quadratic function, is associated with the objective function for minimizing the optimization problem. Therefore, we must first decide how to set weights and input biases for any minimization problem. This process is called "mapping". The sum of the constraints and an objective function are given as inputs to the energy function.

In this paper, the new mapping technique for the Hopfield NN that have been described for quadratic 0-1 programming problems with linear equality and inequality constraints [16] with Abe's formulation [19] for inequality constraints is used. An efficient simulation algorithm has been used to solve the dynamic equation of the Hopfield NN where the time step has been calculated. This approach was proposed for solving the economic dispatch problem by Yalcinoz and Short [1]. In this paper, this approach is applied to the environmentally constrained economic dispatch problem.

The simple quadratic problem without inequality constraints is first considered. The feasible solution for equality constraints can be described as

$$x = T^{constr} x + s \qquad (8)$$

$$\text{where } T^{constr} = I - A^{eq^T} (A^{eq} A^{eq^T})^{-1} A^{eq} \qquad (9)$$

$$\text{and } s = A^{eq^T} (A^{eq} A^{eq^T})^{-1} b^{eq} \qquad (10)$$

For this case, the energy function can be written as

$$E = E^{obj} + \frac{1}{2} c_o \left\| x - (T^{constr} x + s) \right\|^2 \qquad (11)$$

The equality constraints have been combined into a single penalty term in the energy function. The network's weights T and input biases i^b are set as follows for satisfying the energy function (Eq. 11):

$$T = T^{obj} + c_o (T^{constr} - I) \qquad (12)$$

$$i^b = i^{obj} + c_o\, s \qquad (13)$$

where

E^{obj}	:	optimization objective function
x	:	n dimension variable vector of objective function
T^{obj}	:	n x n symmetrical matrix of objective function coefficients
i^{obj}	:	n dimension vector of objective function
A^{eq}	:	equality constraint matrix
b^{eq}	:	m^{eq} dimension equality constraint vector
s	:	feasible subspace offset vector
T^{constr}	:	feasible subspace projection matrix
I	:	identity matrix

The mapping technique can be extended to include the inequality constraints which are converted to equality constraints by introducing slack variables [1]. Weights T and input biases i^b for any minimization process must be defined. We can set the network's parameters as Eq. 12 and Eq. 13. Hence the Hopfield NN is created with n neurons for variables and m^{in} neurons for slack variables.

4. MAPPING OF THE PROBLEM

The environmentally constrained economic dispatch problem is solved using the Hopfield NN method described in Section 3. The objective function of the environmentally constrained economic dispatch problem contains three cost functions, namely the total fuel cost function, the SO_2 emission function and the NO_x emission function. The energy function of the Hopfield neural network contains both the objective function, and equality and inequality constraints. The weights T^{obj} and the input biases i^{obj} of the objective function are set as follows:

$$T_{ii}^{obj} = -2\left(w0\ c_i + w1\ f_i + w2\ k_i\right)$$

and $T_{ij}^{obj} = 0$

$$i_i^{obj} = -\left(w0\ b_i + w1\ e_i + w2\ h_i\right)$$

where b_i and c_i are the cost coefficients of the i-th generator and e_i, f_i, h_i and k_i are parameters estimated on the basis of unit emissions.

A^{eq} and b^{eq} are defined from the load demand equation (eq. 2). Inequality constraints are converted to equality constraints by introducing slack variables [1]. For example, the lower limit of the i-th generator may be converted to equality constraints as:

$$P_i \geq P_{min,i} \quad \Rightarrow \quad P_{min,i} y_k - P_i = 0$$

where $y_k \geq 1$ (y_k is a slack variable of the k-th inequality constraint) and we can define A_k^{in} and b_k^{in} as :

$$\begin{array}{c} A_k^{in} = \begin{bmatrix} 0\ 0 \ldots -1\ 0\ 0 \ldots P_{min,i}\ 0 \ldots 0 \end{bmatrix} \\ \quad\quad\quad\quad \uparrow \quad\quad\quad\quad \uparrow \\ \quad\quad \text{i-th generator} \quad \text{(n+k)-th column} \end{array}$$

and $b_k^{in} = 0$

where

N	:	the number of generators
A^{in}	:	inequality constraint matrix
b^{in}	:	m^{in} dimension inequality constraint vector

T^{constr} and s can be determined using (9) and (10) after finding A^{eq}, A^{in}, b^{eq} and b^{in}. Afterwards we can set new weights and new input biases using (12) and (13).

After the mapping of the problem, the Hopfield NN model is ready to be used for solving the environmentally constrained economic dispatch problem. At this stage, we have to solve the dynamic equation of the Hopfield NN using the simulation algorithm described in [1].

5. SIMULATION RESULTS

In order to validate the proposed procedure, the environmentally constrained economic dispatch was solved for a 3-unit system and for a CIGRE network. The proposed method is implemented with Matlab on a Pentium PC. Here, we have applied the proposed method to the classical economic dispatch, the SO_2 emission dispatch, the NO_x emission dispatch and the emission constrained economic dispatch.

The first test system is a 3-unit power system with a 850 MW demand and with transmission losses. The cost and emission functions coefficients are given in [13]. Transmission losses are calculated using equation (3). The transmission loss coefficients B are given by

$$B = [0.00003\ \ 0.00009\ \ 0.00012]$$

In Table 1, the computational results of the proposed method (PM) for the classical economic dispatch, minimum SO_2 and minimum NO_x are compared with the results of the Taboo Search (TS) and the Hopfield NN (HN) [13]. From the Table 1, it is clear that the classical ED produces a minimum cost dispatch and emissions are higher than the other dispatches. In the SO_2 emission dispatch, SO_2 emission is minimum and the production cost is higher than the other cases. In the NO_x emission dispatch, NO_x emission is minimum and the production costs are better than those of the SO_2 emission dispatch.

From the Table 1, the production costs of the proposed method (PM) are less than those of the HN and the TS for the classical economic dispatch, the SO_2 emission dispatch and the NO_x emission dispatch.

For the SO_2 emission dispatch, the PM provides better solutions than the HN and the TS.

The results of the PM for the emission constrained economic dispatch are shown in Table 2. The production cost is higher than the classical ED and the emissions are higher than the emission dispatches.

The execution time of the PM for the 3-unit system is about 0.02 seconds for all cases..

Table 1. Results of PM, HN and TS

Classical Economic Dispatch (minimum cost)				
		PM	HN [13]	TS [13]
Cost ($/hr)		8334.77	8343.506	8344.598
Emission SO_2 (ton/hr)		9.0294	9.0201	9.02146
Emission NO_x (ton/hr)		0.0995	0.09863	0.09826
Losses P^L (MW)		15.22	15.692	15.798
Power (MW)	P_1	415.88	435.836	435.69
	P_2	324.43	299.365	298.828
	P_3	124.91	130.491	131.28
Emission SO_2 Dispatch (Minimum SO_2)				
		PM	HN [13]	TS [13]
Cost ($/hr)		8384.44	8388.13	8403.485
Emission SO_2 (ton/hr)		8.9633	8.9649	8.974
Emission NO_x (ton/hr)		0.0969	0.0965	0.09768
Losses P^L (MW)		14.33	14.419	15.722
Power (MW)	P_1	541.12	543.651	549.247
	P_2	237.95	226.195	234.582
	P_3	85.26	94.573	81.893
Emission NO_x Dispatch (Minimum NO_x)				
		PM	HN [13]	TS [13]
Cost ($/hr)		8357.43	8363.136	8371.143
Emission SO_2 (ton/hr)		8.9709	8.973	8.986
Emission NO_x (ton/hr)		0.0959	0.09582	0.0958
Losses P^L (MW)		14.26	14.635	15.8
Power (MW)	P_1	502.46	506.816	502.914
	P_2	252.15	250.956	254.294
	P_3	109.65	106.863	108.592

Table 2. Results of the emission constrained ED

Cost ($/hr)		8368.1
Emission SO_2 (ton/hr)		8.9666
Emission NO_x (ton/hr)		0.0962
Losses P^L (MW)		14.39
Power (MW)	P_1	519.26
	P_2	252.33
	P_3	92.80

The second test system is the CIGRE network described in ref. 8. The system has 10 units with a 1750 MW demand and without transmission losses. The proposed method has been applied to the classical economic dispatch, the SO_2 emission dispatch, the NO_x emission dispatch and the emission constrained economic dispatch for the CIGRE test system. The results of the PM are given in Table 3. As the 3-unit system, the classical ED produces a minimum cost dispatch and the emission dispatches produces a minimum emission levels. The emission constrained economic dispatch produces a reasonable results. The average execution time for the CIGRE system is about 1 sec.

Table 3. Simulation results

Classical Economic Dispatch (minimum cost)	
Cost (million $ / hr)	3.7006
Emission SO_2 (ton/hr)	11.0611
Emission NO_x (ton/hr)	3078.9
Emission SO_2 Dispatch (Minimum SO_2)	
Cost (million $/hr)	3.8075
Emission SO_2 (ton/hr)	9.9553
Emission NO_x (ton/hr)	3329.6
Emission NO_x Dispatch (Minimum NO_x)	
Cost (million $/hr)	3.9151
Emission SO_2 (ton/hr)	11.9182
Emission NO_x (ton/hr)	2718.0
Emission Constrained Economic Dispatch	
Cost (million $/hr)	3.7014
Emission SO_2 (ton/hr)	11.0387
Emission NO_x (ton/hr)	3052.2

6. CONCLUSIONS

In this paper, an application of the improved Hopfield neural networks [1] to the environmentally economic dispatch problem has been proposed. The proposed method has been applied successfully to the classical economic dispatch, the SO_2 emission dispatch, the NO_x emission dispatch and the emission constrained economic dispatch. The energy function of the Hopfield NN consists of three functions which are the production cost and emissions functions. The proposed method has been tested on a 3-unit system and a 10-unit system. The results show that this method is capable of being applied to the environmentally economic dispatch problem.

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