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A Novel Neural Network for Economic Load Dispatch with Environmental Constraints

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Abstract: Reliable power production is critical to the profitability of electricity utilities. Power generators need to be scheduled efficiently to meet electricity demand. Economic load dispatch and economic emission dispatch have been applied to obtain optimal fuel cost and optimal emission of generating units, respectively. Combined economic emission dispatch problem is obtained by considering both the economy and emission objectives. The use of orthogonal polynomials will give a very convenient means to obtain the equivalent cost function of the generating units. This method is sufficiently accurate and easy to implement for real time operation and control of power system. A general formulation and the development of Cascade Correlation algorithm to solve the environmentally constrained dispatch problem are presented. The objective is the minimization of the cost of operation, subject to all the usual and emissions constraints. It is shown that the proposed solution technique is capable of yielding good optimal solution with proper selection of control parameters.

Key words: Artificial neural network, cascade correlation, economic dispatch, generation scheduling, optimization and orthogonal polynomial

INTRODUCTION

As competition intensifies in the electricity supply industry, generating companies try to further improve the operating efficiency of their portfolio of power plants. While the application of mathematical optimization techniques has a long history in power system operation, tangible improvements can still be achieved through a more rigorous formulation of the constraints and the application of more robust solution techniques. This study discusses how such improvements can be achieved for the economic dispatch problem, i.e., the optimization of the production of a set of generating units when the environmental constraints along with general constraints of these units are taken into consideration. Since the passage of the U.S. Clean Air Act Amendments 1990, environmental constraints have become of vital concern to system operators[1].

Since the beginning of the power generating enterprise, the basic objective of electric utilities has been the reliable supply of electricity at the lowest possible cost. However, the emphasis on reducing cost has been questioned due to a growing concern over the effects on the environment caused by the emission of pollutants that result from the combustion of fossil fuels in the generation of electric power[2]. In power systems or State Electricity Boards where no Environmental Information Systems (EIS) network is available or in some studies, the EIS network is available but not connected to Load Dispatch Center (LDC), dispatchers usually obtain data about urgent reductions of electricity generation in fossil fueled power plants from the producer or local center of individual power plants to meet the environmental standards.

However, an operating strategy based on only minimum generation cost or minimum emission level is not appropriate for system operation. Therefore, a modified dispatch strategy must be developed that simultaneously considers economic and emission objectives. Economic Emission Power Dispatch (EEPD) optimizes the power generated by thermal units through simultaneously minimizing the generation cost and emission level. In the past, emission-constrained economic dispatch and minimum emission dispatch were proposed. Four emission functions (of NOx, SOx, particulates and thermal pollutants) with suitable weightings are aggregated into a single emission function to solve problems of multiple emissions.

It is customary to have a number of units together at a place rather than having a huge single generator in order to have a better system reliability and convenient maintenance schedule. In order to reduce the

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computational effort, it is better to make available an equivalent cost function of plant involving the units. The use of orthogonal polynomials will give a very convenient means to obtain the equivalent cost function of the generating units[3].

Most of the operations planning tasks of power system reduce to solving combinational optimization problems. An enormous amount of computation is necessary to solve such problems for large power systems. A neural network is composed of many interconnected multiple single output elements; each constituent is called a neuron. A neuron produces a positive output signal when the sum of its input signals exceeds a certain threshold. Otherwise it yields no output.

Many complex, real world problems are characterized as decision making problems with multiple, conflicting and non-commensurable objectives. The main purpose of the optimal power dispatch problem has so far been mainly confined to minimize the total generation cost of a power system. The multiplicity of objectives and the variety of alternatives, it is often desirable to obtain complete knowledge of the decision maker's global preferred structure explicitly represented by perspective decision model. The advances in ANN make it possible to develop and apply the new methodology and technology to extract decision rules from available information in setting of decision making with multiple objectives.

An ANN consists of many highly interconnected simple and similar processing elements neurons operating in parallel to perform useful computation tasks such as recognizing pre programmed or learned patterns. A crucial property of these networks is their ability to improve the performance by learning new information. Among the various learning algorithms cascade correlation is used here.

PROBLEM FORMULATION

The objective of generation scheduling is to minimize the power system operation cost including the cost of fuel for energy generation and starting of process, while satisfying transmission and other system constraints. The traditional Economic Dispatch (ECD) problem assumes that the amount of power to be supplied by a given set of units is constant for a given interval of time and attempts to minimize the cost of supplying this energy subject to constraints on the static behavior of the generating units. Additional system constraints specifying the minimum amount of reserve capacity required are often added to this basic problem. Plant operators, to avoid shortening the life of their equipment, try to keep thermal gradients inside the turbine within safe limits. This mechanical constraint is usually translated into a limit on the rate of increase of the electrical output[4].

Mathematically the optimization problems can be described as follows. The objective of the problem is to minimize

$$F = \sum_{j=1}^{T}\sum_{i\in G} FC_i(P_{ij}) \qquad (1)$$

where $FC_i = a_i{*}P_i^2 + b_i{*}P_i + c_i$

The following are the system and unit constraints, which are taken into account.

- Real power balance Constraint

$$\sum_{i\in G} P_{ij} = P_{Dj} \qquad (2)$$

- Hourly spinning reserve requirements R must be met as

$$\sum_{i\in G} P_{ij}^{max} \geq P_{Dj} + R \qquad (3)$$

- Real power operating limits of generating units

$$P_i^{min} \leq P_{ij} \leq P_i^{max}, i\in G, j\in T \qquad (4)$$

- The transmission line constraints are

$$-P_m^{max} \leq P_{mj} \leq P_m^{max} \qquad m = 1,\ldots, M \qquad (5)$$

$$P_{mj} = \sum_{i\in G} k_{mi} P_{ij} \qquad (6)$$

- The Environmental Constraints are

$$\sum_{i\in G}\left[E_{ij}\left(d_i + e_i P_{ij} + f_i P_{ij}^2\ \right)\ \right] \leq EV_j^{max} \qquad (7)$$

- Implementation of orthogonal polynomials

Suppose there are N units in a plant which are to be combined into a composite unit, then a composite cost curve for unit 1, 2, ..., N can be developed as

$$\begin{aligned} &Fs\ (Ps) = F1\ (P1) + \ldots + F_N\ (P_N) \\ &\text{Where } Ps = \_P1 + \_P2 \ldots + \_P_N \text{. and} \qquad (8) \\ &dF1/\_dP1 = \_dF2/\_dP2 = \_dF3/\_dP3 = \_\ldots = \_\lambda \end{aligned}$$

If one of the units hits limits, its output is held constant. A simple procedure to allow one to generate

Fs(Ps) consists of adjusting λ values from λmin to λmax in specified increments, where

λmin = min [dFi/dPi, i = 1, ..., N]
λmax = max [dFi/dPi, i = 1, ..., N]

At each increment, the total fuel consumption and the total power output for all the units are calculated.

F -	Operating cost of the system
FC_i (P_{ij}) -	Production cost of the thermal unit i in the period j and P_{ij} is the unit power output of the unit i in the j period
T -	Time horizon for 24 h
G -	Number of generating units
R -	Spinning reserve
P_{dj} -	Load demand
P_i^{min} -	Minimum real power output in the i th unit
P_i^{max} -	Maximum real power output in the i th unit
P_m^{max} -	Maximum transmission capacity of line m
a, b, c -	Cost co-efficients
d, e, f -	Emission co-efficients
k_m -	Sensitivity coefficient
E_{ij} -	Emission rate of pollutant
Ev_j -	Emission allowance

ANN IMPLEMENTATION

ANN is a high speed online computational techniques, which are trained through an offline algorithm using example pattern, can provide an output corresponding to a new pattern without any iteration in real time. The cascade correlation network is a constituent algorithm, which is used for generation scheduling.

An ANN may find it difficult to remember and recognize each pattern. Thus, each generating unit is pre scheduled by a separate ANN by virtue of the fact that this study is more efficient than training all the units in advance. Each ANN has one input neuron corresponding to the hourly load and the output layer has 10 neurons. Underestimation and overestimation of load can lead to a failure to provide sufficient reserve or lead to an unnecessary large amount of spinning reserve which in turn leads to higher cost[5].

The cascade correlation algorithm step-by-step

Initial configuration: The algorithm begins with a simple perceptron with N input units and M output units. N and M are chosen on the basis of the problem that the network is to learn.

Initial training: The perceptron is trained on the entire training set {(Vp,Tp) | p = 1, . . . , P }, until the performance of the network is as good as possible. If the desired performance is obtained, the algorithm stops. Otherwise: Start adding hidden units to the network, one by one.

Training of candidates: A pool of candidates for a new hidden unit is generated. This pool emulates a stochastic search in the weight space, which will decrease the risk of inserting a candidate stranded in a local minimum with high error. Each node in the pool of candidates is connected to all input nodes and all previously inserted hidden units. Each of the candidates is trained with the purpose of maximizing some measure of "goodness" of the candidate.

Inserting a new hidden unit: The candidate with the highest score is inserted "for real" in the network as a new hidden unit. The incoming weights to the new hidden unit are then frozen, i.e.,they are not to be changed anymore. The new hidden unit is connected to all output nodes with random weights.

Retraining the network: All the incoming weights to the output units are retrained in order to adjust the weights from the newly inserted hidden unit. If the performance of the network is satisfying after retraining, the algorithm stops. Otherwise: Go to 3.

Cascade correlation neural network architecture: A cascade correlation network consists of input units, hidden units and output units. Input units are connected directly to output units with adjustable weighted connections. Connections from inputs to a hidden unit are trained when the hidden unit is added to the net and are then frozen. Connections from the hidden units to the output units are adjustable consequently[6,7].

Cascade correlation network starts with a minimal topology, consisting only of the required input and output units (and a bias input that is always equals to 1). This net is trained until no further improvement is obtained. The error for each output until is then computed (summed over all training patterns). Next, one hidden unit is added to the net in a two-step process. During the first step, a candidate unit is connected to each of the input units, but is not connected to the output units. The weights on the connections from the input units to the candidate unit are adjusted to maximize the correlation between the candidate's output and the residual error at the output units. The residual error is the difference between the target and the computed output, multiplied by the derivative of the output unit's activation function, i.e., the quantity that would be propagated back from the output units in the back propagation algorithm. When this training is completed, the weights are frozen and the candidate unit becomes a hidden unit in the net. The second step in which the new unit is added to the net now begins. The new hidden unit is then connected to the output units and the weights on the connections being adjustable. Now all connections to the output units are trained. (Here the connections from the input units are trained again and the new connections from the hidden unit are trained for the first time.) A second hidden unit is then added using the same process. However, this unit receives an input signal from the both input units and the previous hidden unit. All weights on these connections are adjusted and then frozen. The connections to the output units are then established and trained. The process of adding a new unit, training its weights from the input units and the previously added hidden units and then freezing the weights, followed by training all connections to the output units, is continued until the error reaches an acceptable level or the maximum number of epochs (or hidden units) is reached.

SOLUTION FOR ECONOMIC DISPATCH

Once the generation in a power system is scheduled, it is necessary to determine the optimal allocation of the system demand among the generating units[8]. Economic dispatch is simple and it is continuous variable optimization process with several sets of constraints. The minimization cost function is transformed into a maximization problem by the reciprocal of the cost function. The economic dispatch, which minimizes subject to the constraints in each time period, is a network flow problem with additional linear constraints. The efficiency of the approach is highly dependent upon the efficiency of the above problem, so we use an efficient algorithm, which exploits the particular structure of such problem to obtain the optimal solution. Several economic dispatches are to be solved in each period the efficiency of the proposed approach can be improved[9].

The proposed techniques are applied to the short-term generation scheduling problem of a modified IEEE 39 bus system consisting of 10 units as shown in Fig. 1. The generating unit parameters are shown in Table 1. The daily change of the concentrations of most air pollutants other than ozone and those formed by atmosphere chemical reactions of other air pollutants, follows closely to the pattern of human activities. Higher concentration is observed in the morning around 8 a.m. to 12 a.m. and in the late afternoon/evening around 4 p.m. to 8 p.m. when more traffic and other activities occur. The lowest concentration occurs at night hours when human activities are usually at their lowest. That means the pollutants concentration due to human activities during the day is higher than at night.

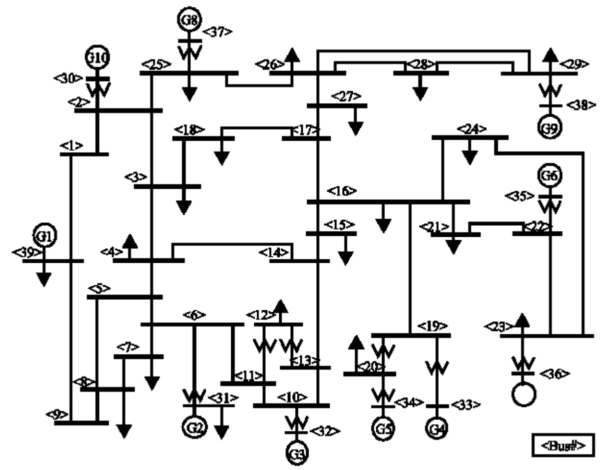

Fig. 1: IEEE 39 bus system

Table 1: Generating unit data

	Coefficients				
Bus no	a_i	b_i	c_i	P_{min}	P_{max}
30(Gen1)	0.074	1.083	100	0	350
31(Gen2)	0.089	1.033	70	0	1145.55
32(Gen3)	0.074	1.083	100	0	750
33(Gen4)	0.089	1.033	70	0	732
34(Gen5)	0.053	1.170	40	0	608
35(Gen6)	0.074	1.083	100	0	750
36(Gen7)	0.089	1.033	70	0	660
37(Gen8)	0.074	1.083	100	0	640
38(Gen9)	0.089	1.033	70	0	930
39(Gen10)	0.053	1.170	40	0	1100

The emission coefficients are the same as those of the corresponding unit fuel cost curves and the emission cap is the same as the peak load, all multiplied by a conversion factor of 0.8. In this study, the transmission lines and environmental constraints are taken into consideration. The generating unit operational data and cost data are obtained from a standard IEEE 39 bus system[10]. In this study, the merit order method is used for dispatching the load amongst the committed units, due to the fact that this method gives better results compared to other methods. The quality and quantity of the fuel depends upon the cost and better fuel will give the good output. Emission of oxides is harmful to the living beings and controlling of emission is required according to the clean air act.

Polynomial reduction of generating units: The IEEE 10 generator 39 bus system is categorized into three areas. Area I comprise of generators 1, 2 and 3, Area II comprises of generators 4, 5, 6 and 7 and Area III comprises of generators 8, 9 and 10.

Assuming all the available units in each area is participating in meeting the system and they are operating within the capacity limits, the

Table 2: Comparative results with BP and CCA

	Load demand in MW											
	1000		2000		4700		4900		5750		6450	
Algorithm	BP	CCA	BP	CCA	BP	CCA	BP	CCA	BP	CCA	BP	CCA
Gen1(MW)	99.17	98.88	197.72	197.71	350	349.95	350	349.98	350	349.98	350	350
Gen2(MW)	82.73	82.50	164.67	164.66	403.16	403.18	424.7	424.69	516.23	516.22	600.4	600.1
Gen3(MW)	99.17	98.88	197.72	197.7	484.54	484.57	510.45	510.43	620.53	620.57	721.71	721.84
Gen4(MW)	82.73	82.50	164.67	164.66	403.16	403.13	424.7	424.73	516.23	516.26	600.4	600.46
Gen5(MW)	137.64	137.24	275.24	275.22	608	607.76	608	607.95	608	607.98	608	608
Gen6(MW)	99.17	98.88	197.72	197.7	484.54	484.56	510.45	510.44	620.53	620.57	721.71	721.84
Gen7(MW)	82.73	82.495	164.67	164.66	403.16	403.17	424.7	424.7	516.23	516.26	600.4	600.53
Gen8(MW)	99.17	98.88	197.72	197.7	484.54	484.56	510.45	510.44	620.48	620.27	640	640.01
Gen9(MW)	82.73	82.50	164.67	164.66	403.16	403.19	424.7	424.68	516.23	516.22	600.4	600.7
Gen10(MW)	137.64	137.24	275.24	275.22	675.17	675.75	711.88	711.85	865.58	865.63	1006.9	1007
Total cost in $	9209.8	9163.4	32196	32192	168720	168710	183670	183660	255730	255720	325890	325880
Total emission in Kg/hr	7367.8	7330.8	25757	25754	134980	134970	146930	146930	204580	204580	260710	260700

Table 3: Comparative results with CCA and CCA with polynomial reduction

	Load demand in MW											
	1000		2000		4700		4900		5750		6450	
Algorithm	CCA	CCAOP	CCA	CCAOP	CCA	CCAOP	CCA	CCAOP	CCA	CCAOP	CCA	CCAOP
Total cost in $	9163.4	9064.6	32192	32096	168710	167340	183660	181600	255720	248740	325880	311970
Total emission in Kg/hr	7330.8	5801.3	25754	20542	134970	107100	146930	116230	204580	159190	260700	199660

equivalent cost function of all the three areas are found by the orthogonal polynomial method.

The reduced equivalent cost functions for the three areas are

Area I
$F_A = 0.047043P_A+1.9230P_A+306.99$

Area II
$F_B = 0.032815P_B+1.9664P_B+503.91$

Area III
$F_C = 0.041268P_C+1.9940P_C+377.94$

Where P_A, P_B and P_C represents the total generation of area I, area II and area III respectively, F_A, F_B, F_C represents the total fuel cost of the area I, area II and area III.

The comparative results for economic load scheduling using back propagation and cascade correlation algorithm are shown in Table 2 for different operating conditions. Table 3 shows the comparative results of the generation scheduling using cascade correlation algorithm and cascade correlation algorithm applied for the generating units with orthogonal polynomials.

CONCLUSION

The cascade correlation algorithm based on ANN is proposed to effectively solve the problem of short-term generation scheduling. The proposed techniques are tested on the IEEE reliability test system consisting of 10 generating units, taking into consideration the system and unit constraints. Two problem formulations are introduced according to the type of fuel cost and start up functions and the group of constraints. With regard to ANN, a long time can be expanded on offline training of the network as ANN accumulates knowledge during offline training from the given input/ output data pairs. However once the network is completely trained, the online response would be very fast compared to analytical programming techniques. It is also expected that the proposed technique can be applied to different problem dimension and could score more favorable compared with analytical techniques.

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