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Neural Based Generation Scheduling 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. This dissertation develops a solution method to schedule units for producing electricity while determining the estimated amount of surplus power each unit should produce taking into consideration the stochasticity of the load and its correlation structure. This scheduling problem is known as the dispatch problem in the power industry. 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. The algorithm handles multiple pollutants and for each pollutant the constraints include the maximum hourly emission on every unit, the maximum hourly emission on every set of on-line units and the maximum daily emission for the system constraints. Three closed-form dispatch strategies and two feasibility conditions are established to eliminate unfeasible unit combinations thus rendering a very efficient commitment algorithm. Test results are provided to show the efficiency of the proposed method.

Key words: Artificial neural network, cascade correlation, economic dispatch, generation scheduling, optimization and unit commitment

INTRODUCTION

Every modern society mandates on adequate supply of electric energy as economically as possible with a reasonable level of quality and continuity. Short term generation scheduling is currently an area of intensive research, especially with the tendency towards privatization and deregulation of power industry. It is a challenging optimization problem because of the complex interplay amongst many variables. Reliable power production is critical to the profitability of electricity utilities[1]. Cost of power production is a significant part of the Gross Domestic Product (GDP) and efficient methods of production can help reduce this cost. Power generated by transforming natural sources of energy, which is used to satisfy societal demands. In general the power-planning problem is based on three different sets of decisions that are dependent on the length of the planning time horizon.

The first set consists of the long-term decisions (years) where the decision variables to be determined are the capacity, type and number of power generators (units) to own. In the medium term (days, weeks), one needs to decide how to schedule (commit) the existing units for the planning horizon. Finally, in the short term (seconds to hours), the goal is to efficiently determine the amount of power each committed unit will produce to meet the real-time electricity demand.

In general, the long-term problem is identified as the power expansion problem, the medium term problem is identified as the Unit Commitment (UC) problem and the short-run problem is called the economic dispatch (generator allocation) problem[2]. The UC problem is solved for time horizons of one day to one week. Once system operators obtain this schedule they solve the economic dispatch problem on a rolling horizon basis using a time window of up to 15 minutes and change the outputs of the committed units to reflect the revised demand estimates.

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 combination as used here.

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

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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. In power systems or State Electricity Boards where no Environmental Information Systems (EIS) network is available or in some cases, 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.

These pollutants include various harmful agents such as Carbon Dioxide (CO_2), Carbon Monoxide (CO) and volatile organic compounds VOC. But the major concern has been the emission of Sulfur-dioxide (SO_2) and Oxides of Nitrogen NO_X, which are considered to be the main source for the production of acid rain. The most important legislation now affecting the electric power sector is the two-phase requirements of the Clean Air Act Amendment (CAAA), which mandates limits on the emission of pollutants[3]. The overall goal of the CAAA is to reduce SO_2 and NO_X emissions by 10 and 20 million tons per year respectively. The NO_X requirements are forcing electric utilities to install low-NO_X burning technology to limit NO_X emission to less than. 45 lb/MMBtu.

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 (TCD) 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.

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

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

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

- Real power balance Constraint

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

- Hourly spinning reserve requirements R must be met as

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

- Real power operating limits of Generating Units

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

- Unit Minimum up/down (MUT/MDT) time is given as

$$(T^{off}_{i,j-1} - MDT_i)(u_{i,j} - u_{i,j-1}) \geq 0 \qquad (5)$$

$$(T^{on}_{i,j-1} - MUT_i)(u_{i,j-1} - u_{i,j}) \geq 0 \qquad (6)$$

- The ramp constraints are

$$-P_m^{max} \leq P_{mj} \leq P_m^{max} \qquad m = 1,\ldots,M \qquad (7)$$

$$P_{mj} = \sum_{i\in G} k_{mi}P_{ij}U_{ij} \qquad (8)$$

- The transmission line constraints are

$$P_{ij} - P_{ij-1} \leq UR_i \qquad (9)$$

$$P_{ij-1} - P_{ij} \leq DR_i \qquad (10)$$

- The Environmental Constraints are

$$\sum_{i\in G}[E_{ij}(d + e_iP_{ij} + f_iP_{ij}^2)] \leq EV_j^{max} \qquad (11)$$

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

Table 1 Generating unit Data

Unit	$P_{i\,min}$	$P_{i\,max}$	a_i	b_i	c_i	Bus
1	2.40	12	0.025	25.547	24.389	15
2	2.40	12	0.026	25.675	24.411	15
3	2.40	12	0.028	25.803	24.638	15
4	2.40	12	0.028	25.932	24.761	15
5	2.40	12	0.029	26.061	24.888	15
6	4.00	20	0.012	37.551	117.755	1
7	4.00	20	0.013	37.664	118.108	1
8	4.00	20	0.014	37.777	118.457	2
9	4.00	20	0.014	37.890	118.820	2
10	15.20	76	0.009	13.327	81.136	1
11	15.20	76	0.009	13.354	81.298	1
12	15.20	76	0.009	13.381	81.464	2
13	15.20	76	0.009	13.407	81.626	2
14	25.00	100	0.006	18.000	217.895	7
15	25.00	100	0.006	18.100	218.335	7
16	25.00	100	0.006	18.200	218.775	7
17	54.25	155	0.005	10.694	142.734	15
18	54.25	155	0.005	10.715	143.028	16
19	54.25	155	0.005	10.737	143.317	23
20	54.25	155	0.005	10.758	143.597	23
21	68.95	197	0.003	23.000	259.131	13
22	68.95	197	0.003	23.100	259.649	13
23	68.95	197	0.003	23.200	260.176	13
24	140.00	350	0.002	10.862	177.057	23
25	100.00	400	0.002	7.492	310.002	18
26	100.00	400	0.002	7.503	311.910	21

pre scheduled by a separate ANN by virtue of the fact that this approach is more efficient than training all the units in advance. Each ANN has 24 input neurons corresponding to the 24 h loads and the output layer has 24 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.

Cascade correlation algorithm: In addition to the probabilistic neural net, cascade correlation is another network that modifies its own architecture as training progresses. It is based on the premise that the most significant difficulty with current learning algorithms (such as back propagation) for neural networks is their slow rate of convergence. This is due, at least in part, to the fact that all of the weights are being adjusted at each stage of training. A further complication is the rigidity of the network architecture throughout training[4]. Cascade Correlation network addresses both of these issues by dynamically adding hidden units to the architecture, but only up to the minimum number necessary to achieve the specified error tolerance for the training set. Furthermore, a two-step weight training process admits that only one layer of weights is being trained at any time. This allows the use of simpler training rules (the delta rule, perceptron etc.) than for multi layer training. In practice, a modification of back propagation algorithm known as Quick Propagation is usually used.

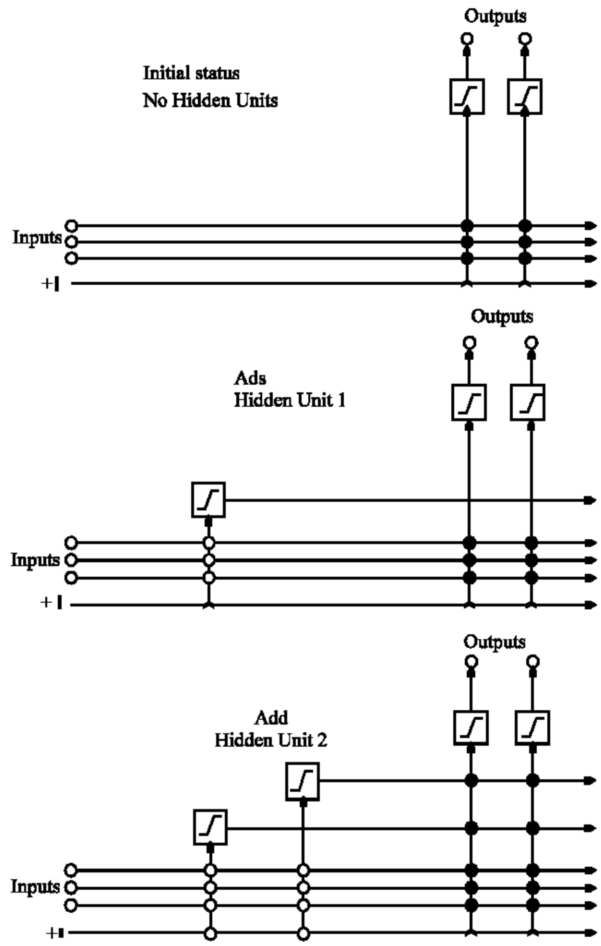

Fig. 1: Cascade architecture initial state and after adding two hidden units. The vertical lines sum all incoming activation. Boxed connections are frozen, X-connections are trained repeatedly

Cascade correlation neural network architecture: A cascade correlation[4] net 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.

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

Table 2: Generating units operating parameters

Units	Min Up H	Min Down H	Initial Conditions H	UH H	DH H	UR MW/h	DR MW/h	α_i h	β_i h	χ_i h
1-5	0	0	-1	0	0	48	60	0	0	1
6-9	0	0	-1	1	0	30.5	70	20	20	2
10-13	3	-2	3	2	1	38.5	81	50	50	3
14-16	4	-2	-3	2	2	51	74	70	70	4
17-20	5	-3	5	3	2	55	78	150	150	6
21-23	5	-4	-4	4	2	55	99	200	200	8
24	8	-5	10	5	3	70	120	300	200	8
25-26	8	-5	10	8	4	50.5	100	500	500	10

$SC_{i,j} = U_{i,j}\{1-U_{i,j-1}\}[\alpha_i+\beta_j[1-\exp\{T^{off}_{i,j}/\tau_j\}]]$

Table 3: Hourly load demand and bus load as percentage of total load

Hour	Load, MW	Hour	Load, MW	Hour	Load, MW	Bus number	Bus load,%	Bus number	Bus load,%
1	2000	10	2257	19	2539	1	3.8	10	6.8
2	1847	11	2308.5	10	2488	2	3.4	13	9.3
3	1744	12	2334	21	2411	3	6.3	14	6.8
4	1693	13	2308.5	22	2360	4	2.6	15	11.1
5	1642	14	2257	23	2231.5	5	2.5	16	3.5
6	1643	15	2231.5	24	2077.5	6	4.8	18	11.7
7	1693	16	2231.5	-	-	7	4.4	19	6.4
8	1795.5	17	2334	-	-	8	6.0	20	4.5
9	2052	18	2565	-	-	9	6.1	-	-

Table 4: Results of ANN with Cascade Correlation Algorithm and Back Propagation

	ANN CCA		ANN BP	
Hours	Cost \$	Emission Kg	Cost \$	Emission Kg
1-3	438702	302270	441128	314523
4-6	433821	302206	439905	319761
7-9	432362	302314	438091	318943
10-12	425724	302415	441008	315691
13-15	434240	301978	438917	318891
16-18	434545	301871	439597	319532
19-21	434344	301981	439072	319589
22-24	429855	302137	435138	320045

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.

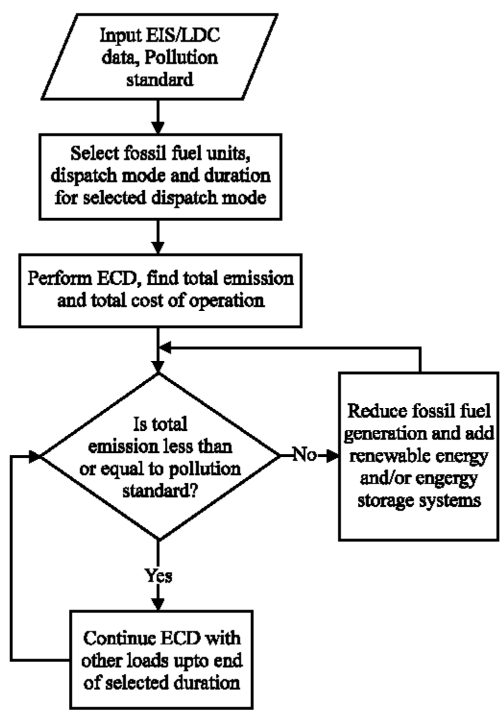

Fig. 2: Functional Flow diagram

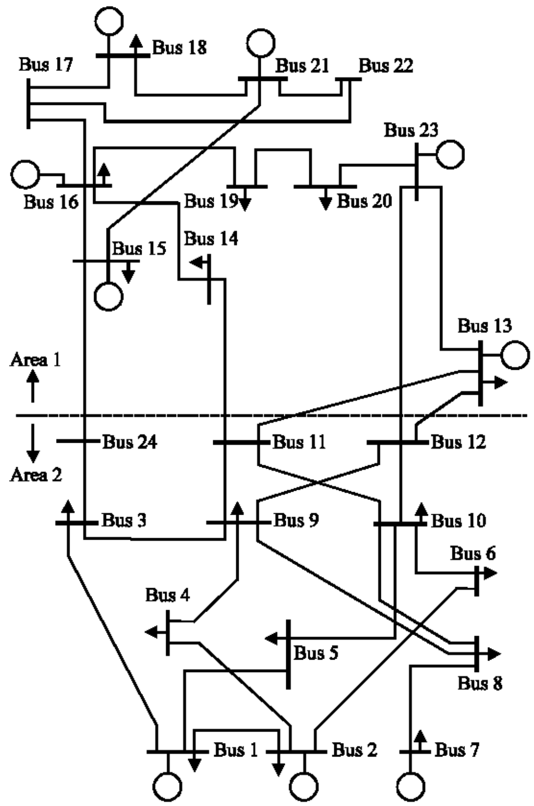

Fig. 3: IEEE 24 Bus System

APPROCH TO 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. 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.

$$F_{GA} = \sum_{j=1}^{T} F(j) + \alpha_1 SC(j) + \alpha_2 SDC(j) + \alpha_3 FTR(j) + \alpha_4 FTD(j) + \alpha_5 VTL(j) \quad (12)$$

where $\alpha_1, \alpha_2, \ldots, \alpha_5$ are penalty factors, SC(j), SDC(j), FTR(j), FTD(j) and VTL(j) are the penalty terms, which are utilized either when a unit does not comply with the minimum up/minimum down time, or fails to meet the reserve and the load demand. 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[5]. Several economic dispatches are to be solved in each period the efficiency of the proposed approach can be improved.

DISCUSSION

The proposed techniques are applied to the short-term generation scheduling problem of a modified IEEE 24 bus system consisting of 26 units[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 to 12 am and in the late afternoon/evening around 4 to 8 pm 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.

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. To facilitate comparing the results of the proposed techniques to other recently reported approaches utilizing Back Propagation (BP). In this case, the transmission lines, ramp rate and environmental constraints are taken into consideration. The generating unit operational data and cost data are obtained from a standard IEEE 24 bus system. In this case, 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.

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 26 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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