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A Hybrid FLN and Lagrangian Relaxation Approach to Generator Unit Commitment*

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Abstract: A hybrid method for achieving the generating unit commitment using a functional link network (FLN) is proposed in this paper. Based on the use of supervised learning neural-net technology and the adaptive pattern recognition concept, the developed FLN was used to presume the relationship between power demand pattern and Lagrange multipliers (LMPs). To demonstrate the effectiveness of the proposed approach, a real power generation system with 16 thermal units was tested. Numerical results show that the system production cost was minimal and the time taken for processing the unit commitment scheduling in power systems was reduced.

Key words: unit commitment; artificial neural networks (ANN); lagrangian relaxation method

1 Introduction

Most of power system operation planning tasks can be finally reduced to solving combinatorial optimization (mixed integer programming) problems that include a number of inequality as well as equality constraints, such as unit commitment, they belong to the class of NP-complete problems. An enormous amount of computation is necessary to solve such problems for large power systems. This emphasizes the strong need for making some breakthrough.

Electric power systems have the following features in common: production is simultaneous with consumption and both surplus and shortage of power supply may cause undesired voltage and frequency. A balance must therefore be maintained between power supply and power demand.

Unit commitment, a power generation scheduling problem, involes determination of the hourly start-up/shut-down schedule and the output levels of all generators in order to meet forecasted hourly demand per day and to minimize total operating costs, the sum of

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setup and fuel costs for a given day. In general, to solve the problem is very difficult and time consuming. Major solution methods proposed so far may be classified as: 1) Dynamic programming [1], 2) Branch and bound method[2], 3) Mixed integer programming[3] and 4) Lagrangian relaxation[4,5].

Among them, method 1)～3) are not practical since computational burden and storage requirement will be dramatically increased with the number of generators. Although the last method is effective to a large power system, it depends on how the values of LMPs are determined.

ANNs possess the ability to perform pattern recognition, prediction and optimisation in a fast and efficient manner after they are sufficiently trained. Applying ANNs to power systems is of rather recent origin[5]. In this paper, the LMPs are estimated by using of the FLN[7]. Numerical results show that the LMPs estimated by the FLN are applicable to the above problem.

2 Problem Formulation

Unit commitment can be defined as to determine an optimal pattern for the start-up and shut-down of generators that minimizes the total operating cost during a study period while maintaining a suitable amount of spinning reserve. Assumptions usually made in solving this problem are[2~5]: 1) Power demand during each period is constant and given; 2) Transmission losses are neglected; and 3) Spinning reserve is specified. Under the above assumptions, unit commitment can be formulated as follows:

Objective function Suppose N is the number of generators, T is the number of periods under study, v_{it} is decision variable for generator

$$J(P,v) = \sum_{i=1}^{N}\sum_{t=1}^{T}[C_i(P_{it}) + S_i(x_{it},v_{it})], \tag{1}$$

where $C_i(P_{it})$ is the presentation cost function of generation output p and $S_i(x_{it},v_{it})$ is the start-up/shut-down cost, expressed as a function of both state variable x_{it} and decision variable v_{it}.

Constraints a) Power balance

$$\sum_{i=1}^{N} P_{it} = D_t, \quad t = 1,2,\cdots,T. \tag{2}$$

b) Limits on generator output

$$v_{it}P_{\min i} \leqslant P_{it} \leqslant v_{it}P_{\max i}. \tag{3}$$

c) Operating constraints:

Minimum up time constraint $\quad v_{it} = 1, \text{for } 0 \leqslant x_{it} < mut(i)$. (4a)

Minimum down time constraint $\quad v_{it} = 0, \text{for } -mdt(i) < x_{it} < 0$. (4b)

3 Lagrangian Relaxation Method

An efficient method for solving the problem is based on a dualization, using the lagrangian relaxation method. The dual function can be formulated by adjoining the demand

and supply balance constraints to the objective function, introducing LMP λ_t. The dual function is expressed by

$$q(\lambda) = \min_{p,v}[J(p,v) + \sum_{t=1}^{T}\lambda_t(D_t - \sum_{i=1}^{N}p_{it})]. \tag{5}$$

We then have the following dual problem

$$\max_{\lambda} q(\lambda), \quad \text{subject to (3) and (4).} \tag{6}$$

In view of the separable structure of $q(\lambda)$, the dual function can be rewritten as

$$q(\lambda) = \sum_{i=1}^{N}q_i(\lambda) + \sum_{t=1}^{T}\lambda_t D_t. \tag{7}$$

where the functional value of q_i determined by solving the following subproblem 1 with LMPs fixed.

Subproblem 1

$$q_i(\lambda) = \min_{p,v}\sum_{t=1}^{T}[C_i(p_{it}) + S_i(x_{it},v_{it}) - \lambda_t p_{it}], \tag{8}$$

subject to (3) and (4).

The LMPs are updated by using the subgradient method.

After the start-up/shut-down schedule is fixed, a continuous problem is economic load dispatch, which could be solved by using the principle of equal incremental fuel cost.

4 The FLN and GI Learning Algorithm

4.1 The FLN Architecture

An FLN is a new network architecture consisting of a flat net with no hidden-layer nodes. The basic idea behind an FLN is the use of links for effecting nonlinear transformations of the input pattern before it is fed to the input layer of the actual network. The essential action is therefore the generation of an enhanced pattern to be used in place of the actual pattern.

The architecture of this type of net is depicted in Fig. 1.

Input patterns are enhanced by nonlinear representation, so a flat net is used with no hidden layers. There are two models for the FLN, namely the functional expansion model and the tensor (or outerproduct) model. Different effects are obtained depending on the details of the model used. Also the models may be used in tandem to great effect.

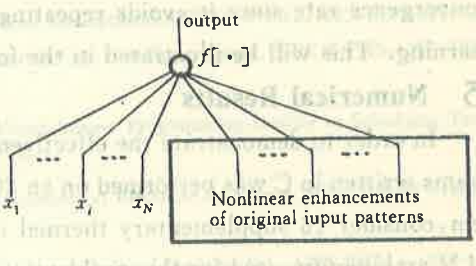

Fig. 1 Schematic illustration of the functional-link net

4.2 GI Learning Algorithm

Let us consider the possibility of learning with a flat net. After the input patterns are expanded, a single layer neural-net is merely constructed. Let there be P associated input-output pattern pairs, $(\overline{X}_1,\overline{Y}_1),(\overline{X}_2,\overline{Y}_2),,\cdots(\overline{X}_P,\overline{Y}_P)$, each with N elements, where $\overline{X}_i$ has been expanded ($i = 1,2,\cdots,P$), which is associated with the output by the matrix $M = (M_{ij})$. That is

$$M\overline{X}_k = \overline{Y}_k, \quad k = 1,2,\cdots,P. \tag{9}$$

Let

$$X = (\overline{X}_1,\overline{X}_2,\cdots,\overline{X}_P), \quad Y = (\overline{Y}_1,\overline{Y}_2,\cdots,\overline{Y}_P).$$

Thus the equation (1) becomes

$$MX = Y. \tag{10}$$

Using the Moore-Penrose GI method, we then have

$$M = YX^*, \tag{11}$$

where "$*$" indicates GI.

Computer realization of M is obtained through numerical recursion. Let

$$X^{(k)} = (X_1,\cdots,X_k), \quad Y^{(k)} = (Y_1,\cdots,Y_k), k = 1,2,\cdots,P$$

thus k th recursion of M is as follows

$$M^{(k)} = Y^{(k)}X^{(k)*} = M^{(k-1)} - M^{(k-1)} - \overline{X_k b_k} + \overline{Y_k b_k}. \tag{12}$$

where

$$\overline{b}_k = \begin{cases} (\overline{C}_k^T C_k)^{-1}, & \overline{C}_k \neq 0, \\ (C_1 + \overline{d}_k^T \overline{d}_k)^{-1} \overline{d}_k^T X^{(k-1)^*}, & \overline{C}_k = 0, \end{cases} \tag{13}$$

$$\overline{C}_k = \overline{X}_k - X^{(k-1)}\overline{d}_k, \tag{14}$$

and

$$\overline{d}_k = X^{(k-1)} + \overline{X}_k. \tag{15}$$

The first pair $(\overline{X}_1,\overline{Y}_1)$ is fed to the FLN to yield the initial recursion value of M, that is

$$M^{(1)} = \overline{Y}_1(\overline{X}_1^T\overline{X}_1)^{-1}\overline{Y}_1^T. \tag{16}$$

Thus M is obtained through recursion until all patterns are memorized, via P recursions. So $M = M^{(P)}$. Therefore if P pairs of patterns are available to be fed to the FLN, the associated matrix M can be obtained. Compared to the delta rule, the method has a faster convergence rate since it avoids repeating the presentation of input patterns in delta rule learning. This will be illustrated in the following section.

5 Numerical Results

In order to demonstrate the effectiveness of the proposed method, the simulation programs written in C was performed on an 80486 DX—80mhz. For the Guangzhou power system, consider 16 supplementary thermal units ($N = 16$) over 24 ($T = 24$) periods. The FLN architecture used for this problem consists of input and output layers with 24 original input/output nodes, respectively. Proper training is a vital part of the application of FLN. For training purposes the training set $\{D,\lambda\}$ must be prepared according to past records. The set can also be obtained from application of the Lagrangian relaxation method to the presentative power demand patterns. The selected load demand profiles represent typical operating circumstance of the studied power systems. Since the output from each neuron is determined by the sigmoidal logistic function, each element of a training pair must be normalized between 0 and 1. The final output levels are shown in Table 1.

Table 1 The final output levels (units: MW)

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48	48
2	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46
3	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	39	39	39	39	39	39	39	39	41	41	41	41	41	41	40	40	40	40	40	42	42	40	38	38
6	40	40	40	40	40	42	42	42	42	42	42	41	35	37	40	40	40	40	40	40	40	39	38	38
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	28	28	28	28	28	28	28	28	28	28	30	30	26	26	28	28	28	28	28	30	32	26	26	26
9	34	30	30	25	25	32	32	34	34	34	34	34	32	32	32	32	32	32	32	35	35	32	30	28
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	25	25	24	24	24	24	27	27	27	27	27	27	25	25	25	25	26	26	28	28	28	24	24	24
12	15	15	15	15	16	16	16	18	18	18	18	18	18	18	18	18	18	18	18	18	18	16	16	16
13	0	0	0	0	22	22	22	22	22	22	22	22	22	22	22	22	24	24	24	24	24	24	0	0
14	0	0	0	0	10	10	10	10	12	12	12	14	14	12	12	12	12	12	12	14	14	12	10	8
15	11	0	0	0	11	11	13	13	13	13	13	13	13	13	13	13	13	13	13	14	14	12	0	0
16	7	0	0	8	8	8	8	8	8	10	10	10	10	10	10	10	10	10	10	10	12	12	8	7

6 Conclusion

In prcatice, the short term unit commitment often requires a method that is fast to meet system changes and reduces the scheduling errors. With a trained FLN, a fast and direct assessment of LMPs has been obtained. The numerical results indicate that the present method provides and alternative for unit commitment practices.

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混合 FLN-Lagrange 松驰法用于机组最优投入

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摘要：本文提出用混合函数链网络与 Lagrange 松驰法解机组最优投入问题. 基于神经网络的监督学习和自适应模式识别概念，FLN 被用来预测负荷需求与 Lagrange 乘子之间的关系. 为了证实这一方法的有效性，一个具有 16 台电机组的实际系统被测试. 数值计算结果表明系统发电总成本可获得最少，大大减少了计算时间.

关键词：机组优化组合；人工神经网络；Lagrange 松驰法

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张潮海 1963 年生. 1985 年毕业于哈尔滨工业大学，1988 年在海军航空工程学院获硕士学位. 现为华南理工大学自动化系博士生，主要研究兴趣为神经网络、电力系统运行与控制等.

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