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A dynamic programming based fast computation Hopfield neural network for unit commitment and economic dispatch

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Abstract

This paper develops a new dynamic programming based direct computation Hopfield method for solving short term unit commitment (UC) problems of thermal generators. The proposed two step process uses a direct computation Hopfield neural network to generate economic dispatch (ED). Then using dynamic programming (DP) the generator schedule is produced. The method employs a linear input–output model for neurons. Formulations for solving the UC problems are explored. Through the application of these formulations, direct computation instead of iterations for solving the problems becomes possible. However, it has been found that the UC problem cannot be tackled accurately within the framework of the conventional Hopfield network. Unlike the usual Hopfield methods which select the weighting factors of the energy function by trials, the proposed method determines the corresponding factor using formulation calculation. Hence, it is relatively easy to apply the proposed method. The Neyveli Thermal Power Station (NTPS) unit II in India with three units having prohibited operating zone has been considered as a case study and extensive study has also been performed for power system consisting of 10 generating units.

Keywords: Unit commitment; Economic dispatch; Hopfield network; Optimization; Dynamic programming

1. Introduction

The unit commitment problem schedules the available generators to meet the required load subject to various constraints. The UC plays a major role in power systems operation and control. The unit commitment has commonly been formulated as non-linear, mixed integer, large-scale combinatorial problem for providing the best generating unit schedule and minimizing the operating cost of power system. The economic dispatch problem (EDP) optimally allocates the load demand among the running units while satisfying the power balance equations and unit operating limits [1]. Reviews of unit commitment problem (UCP) may be found in Ref. [2]. The solution methods being used to solve the unit commitment problem can be divided into three categories.

- Optimization method such as dynamic programming [3,4] mixed integer programming, branch and bound [5] and Lagrangian relaxation [6,7].
- Heuristic methods such as priority list [8].
- Artificial intelligence methods such as neural networks [9] genetic algorithms [10,11], expert systems [12], simulated annealing [13], evolutionary programming [14,15] and Tabu search [16].

The dynamic programming method [3,4] based on a priority list is flexible, but the computational time suffers from dimensionality. The shortcoming of branch and bound method [5] is that the execution time increases rapidly for large-scale UC problem. The Lagrangian relaxation (LR) method [6,7] provides a fast solution but it suffers from numerical convergence and solution quality. The priority list method [8] is simple and fast, but the quality of final solution is quite far from the optimum.

With the advent of artificial intelligence approaches, genetic algorithm (GA), evolutionary programming (EP), simulated annealing (SA), Tabu search (TS) and expert systems (ES) have been proposed to solve the UC problem. GA, EP and TS require

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a considerable amount of computational time, especially for a large system. One draw back of SA is that it takes much of CPU time to reach a near global minimum.

Due to the use of the sigmoidal function in the conventional Hopfield method to solve UC problems, the numerical iteration method is inevitably applied though the numerical iteration method often suffers from large amount of computational requirement [17]. Further, adopting the modified sigmoidal function causes incorrect generation dispatch and selecting shape constant is troublesome.

To avoid the aforementioned problems, a linear model describing the input–output relationship is proposed. The proposed method is different from all Hopfield methods previously reported. All previously presented Hopfield methods apply the iterative procedures requiring a large quantity of computation to arrive at accurate solutions. However based on the formulations developed the proposed method computes its solutions analytically and no iteration is needed in the solving process. Consequently, computational efforts are greatly reduced.

Determination of weighting factors is relatively simple for the proposed analytic method, because the value of the corresponding factor is determined using straightforward calculation. It can be determined regardless of the power mismatch and converging speed selected.

The proposed dynamic programming based Hopfield neural network (DPHNN) is a hybrid of intelligence system and traditional mathematical programming. With its two steps processing, the algorithm can benefit from the advantages of both the methods. The proposed DPHNN method has been applied to NTPS 7 unit system and 10 unit system. Computational results from the proposed method are compared with other methods.

2. Unit commitment problem

The unit commitment problem can be mathematically described as follows:

$$\text{Min } F_i(P_i^t) = \sum_t \sum_i [(a_i + b_i P_i^t + c_i (P_i^t)^2) + ST_{i,t}(1 - U_{i,t-1})]U_{i,t} \tag{1}$$

where $F_i(P_i^t)$ is the generator fuel cost function in quadratic form, a_i, b_i and c_i the coefficients of unit i, P_i^t the power generation of unit i at time t and $U_{i,t}$ is the on/off status of unit i at time t.

Subject to the following constraints:

(a) Power balance constraint

$$\sum_i P_i^t U_{i,t} = P_{\text{D}}^t + P_{\text{L}}^t \tag{2}$$

$$P_{\text{L}} = \sum_{i=1}^{N} B_i P_i^2 \tag{3}$$

where P_{D}^t is the total load demand at time t, P_{L}^t the power loss at time t, B_i the coefficients of power loss and N is the total number of generator units.

(b) Spinning reserve constraint

$$P_{\text{D}}^t + R^t - \sum_{i=1}^{N} P_{i,\max} U_{i,t} \le 0 \tag{4}$$

where R^t is spinning reserve constraint at time t.

(c) Generation limit constraint

$$P_{i,\min} \le P_i^t \le P_{i,\max} \tag{5}$$

where $P_{i,\min}$ is the minimum generation limit and $P_{i,\max}$ is the maximum generation limit.

(d) Generation limits for units with prohibited zones.

There exist some prohibited operating zones [18] in the cost curve due to steam valve operation or vibration or the shaft bearing. Practically, it is very difficult to determine the shape of the cost curve in the prohibited zone. Walters and Sheble [19] model uses a rectified sinusoid function to show the effects of a prohibited zone. The best economy is achieved by avoiding operation in these areas. This paper deals with this effect using an inequality constraint.

$$\begin{aligned} &P_{i,\min} \le P_i \le P_{i,1}^{\text{l}} \quad \text{or} \quad P_{i,j-1}^{\text{u}} \le P_i \le P_{i,j}^{\text{l}} \\ &(j = 2, \ldots, ni) \quad \text{or} \quad P_{i,ni}^{\text{u}} \le P_i \le P_{i,\max} \forall i \in \omega \end{aligned} \tag{6}$$

where $P_{i,j}^{\text{l}}$ is lower bound of the jth prohibited zone in unit i, $P_{i,j}^{\text{u}}$ the upper bound of the jth prohibited zone in unit i, ni the number of prohibited zones in unit i, and ω is set of all on-line units that have prohibited operating zones.

(e) Minimum up and down time constraint

$$U_{i,t} = \left\{ \begin{array}{ll} 1, & \text{if } T_{i,\text{on}} < T_{i,\text{up}} \\ 0, & \text{if } T_{i,\text{off}} < T_{i,\text{down}} \\ 0 \text{ or } 1, & \text{otherwise} \end{array} \right\} \tag{7}$$

where $T_{i,\text{up}}$ is minimum up time, $T_{i,\text{down}}$ the minimum down time, $T_{i,\text{on}}$ the continuously on time and $T_{i,\text{off}}$ is the continuously off time of unit i.

(f) Start-up cost

$$\text{ST}_{i,t} = S_{\text{oi}}\,[1 - D_i\,\mathrm{e}^{(-T_{i,\text{off}}/T_{i,\text{down}})}] + E_i \tag{8}$$

where S_{oi} is cold start-up cost, D_i and E_i are start-up cost coefficients for unit i.

(g) Units initial status and

(h) Must run constraint.

3. Conventional Hopfield method

The Hopfield model is a mutual coupling neural network and non-hierarchical structure. The dynamic characteristic of each neuron can be described by the following differential equation

$$\frac{\mathrm{d}U_i}{\mathrm{d}t} = \sum_j T_{ij} V_j + I_i \tag{9}$$