ECONOMIC DISPATCH OF POWER TRANSMISSION LOSSES MINIMIZATION BY PENALTY-FUNCTION NONLINEAR PROGRAMMING NEURAL NETWORK METHOD

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Abstract

This study will provide an account on the use of penalty-function nonlinear programming neural network method to find the optimal power generating output which can minimize both the power generating cost and power transmission losses. This method is an adaptation of neural network technology in acquiring exterior penalty function. For the nonlinear functions in equality and inequality constraints, model is built up model by neural network and additional objective functions; this additional target function expands cost function using suitable penalty function. In this study, 26-busbar including 3 generators was used to test for the penalty function nonlinear programming neural network method. Traditional non-constrained optimization technique will be compared here in order to demonstrate the reliability and precision of the optimal solution can be obtained from our method.

1. Introduction

The introduction of power market deregulation mechanism has brought significantly influenced on the power is generated, transmitted and distributed in the power market, which has existed for over a hundred years. Its main purpose is to break off traditional monopoly; and as more regional power generating markets are established, power generation efficiency is expected to increase. All power companies therefore need to devise a effective time control on the generator electricity supply to minimize the generating cost and transmission losses while maintaining operation at the desired security levels. In the kinds of economic dispatch problem there are two types of objective functions the fuel cost objective function and the real power losses object function. In other words, the solution to this problem is to acquire the optimal generating output that could both minimize the fuel costs and real power transmission losses. The current power generating system dispatch relies on real-time experiential algorithm for executing the economic dispatch and the operation at the desired security level; that makes simulations involving real communications between computer controller and power operator become necessary. Past literature[1] describes the use of a nonlinear programming method to solve this type of economic dispatch problem. To satisfy the equality constraints of 'supply and demand power balance' and the inequality constraints of 'generator operational restriction', the traditional method was to use the exterior penalty-function method. However, most nonlinear designs require extensive amount of computations, and do not apply to situations when real-time or close to real-time optimization results are required. On the other hand, a large penalty constant might result in oscillation of objective function at the boundary. Therefore, we will provide a method in this study, which is to combine penalty function and neural network to increase the level of convergence and shorten the time of calculation, so that the precision of real-time simulation results can be improved. The 26-busbar test system including 3 generators will be used in the study to test this method.

In the second section we will talk about economic dispatch formulation, while in the third the method of exterior penalty function in. A description on the penalty-function nonlinear programming neural network method will be provided in the fourth section. The fifth section will be the description of the simulation test as an example and its results discussed; finally it is the conclusion.

2. Economic Dispatch formulation

Below we will demonstrate the objective function at each dispatch stage. To simplify the model, here we use 2nd order function to demonstrates the relationship between the cost and the generator output per hour; the output of each generator is the result of economic dispatch in the previous hour. The dispatched value of generation in 5 minutes ahead is decided in advance; all time intervals of 5-minute steps to 1 hour ahead and all time intervals up to 1 hour ahead are both decided in advance. Therefore the minimal generating cost will be the objective function here to decide the generating output. The formula model is as follow.

Objective function: minimal generating cost per hour

$$\text{minimize } f(x) = \min \sum_{i=1}^{N_g} C_i(P_i) = \min \sum_{i=1}^{N_g} (a_i P_i^2 + b_i P_i + c_i) \quad (1)$$

Here N_g refers to the number of operators; P_i is the output of generating unit of generator i; a_i, b_i, c_i are coefficients of P_i.

Subject to:

(1)Supply and demand power balance

Assume we don't ignore transmission losses, here we will take transmission losses as a penalty factor to be included in an objective function.

$$\sum_{i}^{N_g} P_i + P_{loss} - L_{load} = 0 \quad \text{for} \quad i = 1,2,\cdots,N_g \qquad (2)$$

L_{load} refers to total load per hour; P_{loss} refers to transmission losses. General transmission loss formulas adapt Kron's loss type and can be presented as follows:

$$P_{loss} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_i B_{ij} P_j + \sum_{i=1}^{N_g} B_{0i} P_i + B_{00} \quad (3)$$

Here, B_{ij}, B_{0i}, B_{00} are losses coefficients and are assumed to be constants.

(2) Constraints on generator operations

$$P_{i,min} \le P_i \le P_{i,max} \quad \text{for } i = 1,2,\cdots,N_g \quad (4)$$

Here $P_{i,min}$ represents the minimized output of generator i; $P_{i,max}$ the maximal output of generator i.

3. Exterior Penalty-Function Method

The current solutions to the constrained nonlinear optimization problems are Kuhn-Tucker and Lagrange multipliers [2-3]. Traditionally, Kuhn-Tucker requires many constraints to acquire the limited extreme value, although the searching range of the optimal solution narrowed down, this nevertheless complicates the process of acquiring the minimal objective function. On the other hand, in the traditional Lagrange multipliers method, it is uneasy to set up the initial value of the multiplier; the value of the objective function often oscillates, the direction to search for the minimized objective function becomes hard to detect resulting decrease of the level of convergence. Therefore we will use the idea of Lagrange [2-3] expansion to convert a constrained problem into a non-constrained problem. Then by adjusting penalty factor, the objective function will gradually reach the optimal solution. This is called the (Sequential Unconstrained Minimization Technique, SUMT) SUMT[2-3]". We will use exterior penalty-function methods to convert constrained optimization problems into unconstrained problems. It can be presented as below:

Minimal objective function: $f(\mathbf{x})$ (5)

Subject to:

Equality constraints: $g_\ell(\mathbf{x})=0 \quad \ell=1,2,\ldots,m.$ (6)

Inequality constraints: $h_j(\mathbf{x}) \ge 0, j=1,2,\ldots,p.$ (7)

Here, $\mathbf{x}=(x_1,x_2,\cdots,x_n)^T \in R^n$, $f(\mathbf{x})$: $R^n \rightarrow R^n$; $g(\mathbf{x})$: $R^n \rightarrow R^m$ are given functions. The $g(\mathbf{x})$ is defined as $g_1,g_2,\cdots,g_m$. $h(\mathbf{x})$: $R^n \rightarrow R^p$ is a given function; the $h(\mathbf{x})$ here is defined as $h_1,h_2,\cdots,h_p$. f、g and h are assumed twice continuous differentiable functions. To deal with the constrained optimization problem mentioned above, the sequential unconstrained minimization techniques (SUMT) can be used to establish a pseudo-objective function. It can be presented as below:

$$\phi(x,K) = f(x) + K \times F(x) \quad (8)$$

Here, $f(\mathbf{x})$ is the original objective function; K is a multiplier, a positive constant to determine the magnitude of the penalty. $F(\mathbf{x})$ is a penalty function, which is a continuous nonnegative function. The penalty function in this study can be presented as follows:

$$F(x) = \sum_{\ell=1}^{m} g_\ell^r(x) + \sum_{\ell=m+1}^{p} h_j^s(x) \quad (9)$$

Here, r, s ≥ 0 is assumed. Therefore, SUMT combines penalty parameter K and constrained function, with simple rule change to the penalty parameter K, to acquire the optimal solution. Therefore as long as the K value is large enough and larger than zero, as the value regularity increases (in the study, increased by the power product of 10), the function of the penalty will increase.

Therefore, this dispatch problem of acquiring the optimal power generating output that can both minimize operating cost and real power transmission losses, the objective function of Eq. (1) and the constrained problems of Eqs. (2) to (4) can be converted into non-constrained minimizing problem:

$$\min \ \phi(P,K) = \min\{ \sum_{i=1}^{N_g} C_i(P_i) + K_0 \times [\sum_{i=1}^{N_g} P_i - P_{load} - P_{loss}]^r + \sum_{i=1}^{N_g} K_i \times [(P_{i,max} - P_i)]^s + \sum_{i=N_g+1}^{2\times N_g} K_i \times [(P_i - P_{i,min})]^s \} \quad (10)$$

The initial conditions of SUMT in this study are:

1. Set P_i, for $P_{i,min} \le P_i \le P_{i,max}$, $i=1,2,\cdots,N_g$
2. Set initial penalty factor $K_i = 10$, $i=0,1,2,\cdots,2\times N_g$
3. Set r=4, s=2

Use Eq. (9), and gradually add up the value of K_i to acquire the optimal solution.

4. Neural Networks in Penalty-Function Nonlinear Programming

The first step to use neural networks [4] to solve a constrained nonlinear programming problem is to define an energy function, so that it can be converted into a non-constrained optimization problem. The energy function used here is defined by exterior penalty-function method; it can be presented as below:

$$E(x) = f(x) + R \times \{ \sum_{\ell=1}^{m} g_i^r(x) + \sum_{\ell=m+1}^{p} h_\ell^s(x) \} \quad (11)$$

Here, R is a penalty parameter. For $\mathbf{x}$, the calculation of gradient of the energy function in Eq. (10) can be presented below, as shown in Eq. (11).

$$\nabla_x E(x) = \left[\frac{\partial E(x)}{\partial x_1} \ \frac{\partial E(x)}{\partial x_2} \ \cdots \ \frac{\partial E(x)}{\partial x_n} \right]^T \quad (12)$$

$$= \frac{\partial f(x)}{\partial x} + R \times [\sum_{\ell=1}^{m} \frac{\partial g_i(x)}{\partial x} \times r \times g_\ell^{r-1}(x) + \sum_{\ell=m+1}^{p} \frac{\partial h_\ell(x)}{\partial x} \times s \times h_\ell^{s-1}(x)]$$

Here we adapt the steepest descent approach. Our learning rule can be presented as:

$$x(t+1) = x(t) - \mu \{ \frac{\partial f(x)}{\partial x} + R \times \sum_{\ell=1}^{m} \frac{\partial g_\ell(x)}{\partial x} \times r \times g_\ell^{r-1}(x) + R \times \sum_{\ell=m+1}^{p} \frac{\partial h_\ell(x)}{\partial x} \times s \times h_\ell^{s-1}(x) \} \quad (13)$$

Here, $\mu > 0$ is the learning rate parameter; t is the index of iterated number. This research on economic dispatch initially sets r=2,s=1, $P_{i,min} \le P_i \le P_{i,max}$, $i = 1,2,\cdots,N_g$ and R= 10^6. As we know, a large penalty constant value might result in the algorithm oscillations at the boundary during the acquiring process, therefore under this condition the value of learning rate parameter μ has to be decreased for the purpose of convergence. Here we set $\mu = 2.5 \times 10^{-6}$; the penalty function of neural network architecture realization can be shown as in Figure 1.

5. Simulation Result

SUMT and this method are both written in Matlab formulas. This study uses 26-busbar containing 3 generators [5] to verify the calculating efficiency of this method to be the same as the optimal generating cost, the optimal real power transmission losses rate shown in the 2nd entry in the bibliography . The fuel cost function per generator per hour is shown in Table 1[5]. The real power operational restriction for each generator is shown in Table 2[5]. The Kron's loss coefficients were calculated by the Newton-Raphson's method [5]. The results for final loss coefficients is presented below:

$$B = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_0 = 10^{-3} \times \begin{bmatrix} -0.3908 & -0.1297 & 0.7047 & 0.0591 & 0.2161 & -0.6635 \end{bmatrix}$$

$$B_{00} = 0.0056$$

In order to compare the difference between this method and SUMT, the two algorithms were executed on the same PC, using the same framework of the system database, and acquiring the same level of convergence. The result is presented in Table 3(a)-3(b). Table 3(a) lists the comparison of the two results of calculation, including the minimal generating cost, minimal real power rate transmission losses, iterated number needed to convergence and the CPU time. From Table 3(a) it is clear that the generating cost and transmission losses of this method are smaller than that of SUMT, which indicates the former to be a better method to deal with this economic dispatch problem. By comparing the iterated number needed to convergence and the CPU time, we know that SUMT has fixed iterated step and that to raise penalty parameter K can increase the reliability of convergence and calculation efficiency. However, oscillation at convergence is likely to occur and therefore affect the calculation efficiency. Therefore if the total load remains the same and the optimal penalty parameter(R and K_i) remains the same in the Table 3(b), the calculation efficiency are the same for both algorithms. With our method, the same total load and the optimal penalty parameter R value, by lowering learning rate parameter μ the precision and the reliability of convergence can be increased, but the calculation efficiency will decrease. But if R value can be properly increased, the calculation efficiency will increase too without affecting the reliability of convergence. On the other hand, SUMT in economic dispatch problems requires very large penalty parameter K_i, furthermore, different constraints require different values of penalty parameters. So K_i value has to be increased individually for the optimal solution. While with our method it is not necessary to have a large penalty parameter R; and the penalty parameter value for the whole system is the same.

If total load changes, SUMT requires more time on adjusting K_i value and more trial-error iterated time. But our method does not require the adjustment of R value and learning rate parameter μ; it can therefore be applied to the real-time calculation. Figures 2 and 3 show the levels of convergence during the variable acquiring process of the two algorithms; it is clear that our method achieved better level of convergence and its optimal solution obtained is better than that of SUMT.

6. Conclusions

The method provides exterior penalty function, to acquire the solutions for a series of linear and nonlinear nonconstrained minimization problems through neural networks. From the simulation results the following conclusion can be made:

1. The SUMT method requires increasing penalty parameter value individually to reach higher level of convergence. However, the adjustment of penalty parameters to satisfy constraints will take a lot more time for calculation and trail-error iterated time. Furthermore, larger penalty parameter value is likely to make the acquiring process ill-conditioned.
2. Our method, while dealing with economic dispatch problem, does not require adjustment of penalty parameter and learning rate parameter μ to follow the total load changes. Therefore convergence can be reached rapidly. This characteristic makes it a very suitable candidate to be applied to real time dispatch situations.

7. References

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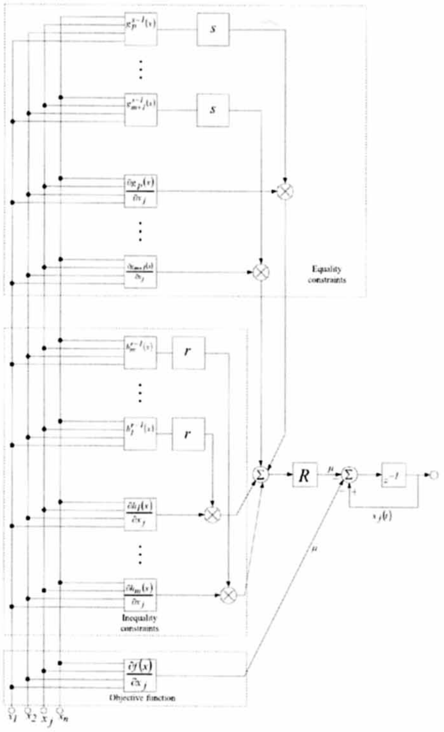

Fig. 1 Penalty function of neural network architecture

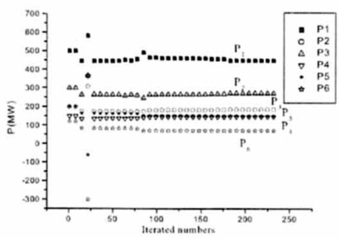

Fig. 2 Trajectories of the generating output for the SUMT solution

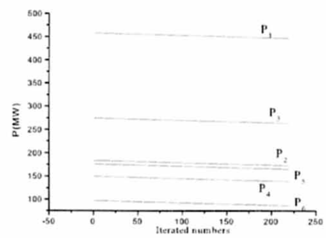

Fig. 3 Trajectories of the generating output for the penalty function nonlinear programming neural network solution

Table 1 The fuel cost function in \$/hr of six units of the test system

Cost (\$/hr)	Function
$C_1(P_1)$	$240+7.0P_1+0.0070P_1^2$
$C_2(P_2)$	$200+10.0P_2+0.0095\ P_2^2$
$C_3\ (P_3)$	$220+8.5\ P_3+0.0090\ P_3^2$
$C_4\ (P_4)$	$200+11.0\ P_4+0.0090\ P_4^2$
$C_5\ (P_5)$	$220+10.5\ P_5+0.0080\ P_5^2$
$C_6\ (P_6)$	$190+12.0\ P_6+0.0075\ P_6^2$

Hint: Load=1275.8MW

Table 2 The constraints on generator operations of the test systems

Item	SUMT	Neural network
P_1 (MW)	449.2772	447.1601
P_2 (MW)	185.3756	173.2001
P_3 (MW)	272.2540	264.0301
P_4 (MW)	145.7849	138.7159
P_5 (MW)	151.6962	165.8437
P_6 (MW)	71.4129	86.7173
P_L (MW)	0.1281	0.1260
Fuel cost (\$/hr)	15456	15450
Iteration numbers	235	544
Computing time (s)	0.49	0.49

Table 3(a) The result of simulation

Variable (MW)	Limits		Initial condition
	Lower	Upper	
P_1	100	500	460
P_2	50	200	185
P_3	80	300	275
P_4	50	150	150
P_5	50	200	180
P_6	50	120	100

Table 3(b) The optimal penalty parameter of the test system

Optimal penalty parameter value											
K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}	K_{12}
480	200	300	440	100	100	100	100	100	100	100	100

Hint:K_0=1.0e+12,R=1.0e+06