Profit-based Thermal Unit Maintenance Scheduling under Price Volatility by Reactive Tabu Search

Junjiro Sugimoto* and Ryuichi Yokoyama†

Abstract – In this paper, an improved maintenance scheduling approach suitable for the competitive environment is proposed by taking account of profits and costs of generation companies and the formulated combinatorial optimization problem is solved by using Reactive Tabu search (RTS). In competitive power markets, electricity prices are determined by the balance between demand and supply through electric power exchanges or by bilateral contracts. Therefore, in decision makings, it is essential for system operation planners and market participants to take the volatility of electricity price into consideration. In the proposed maintenance scheduling approach, firstly, electricity prices over the targeted period are forecasted based on Artificial Neural Network (ANN) and also a newly proposed aggregated bidding curve. Secondary, the maintenance scheduling is formulated as a combinatorial optimization problem with a novel objective function by which the most profitable maintenance schedule would be attained. As an objective function, Opportunity Loss by Maintenance (OLM) is adopted to maximize the profit of generation companies (GENCOS). Thirdly, the combinatorial optimization maintenance scheduling problem is solved by using Reactive Tabu Search in the light of the objective functions and forecasted electricity prices. Finally, the proposed maintenance scheduling is applied to a practical test power system to verify the advantages and practicability of the proposed method.

Keywords: Maintenance Scheduling, Tabu Search, Electricity Market, Electricity Price Forecasting, Artificial Neural Network.

1. Introduction

The electric industry throughout the world, which has long been dominated by vertically integrated utilities, is undergoing enormous changes. The electric industry is evolving into a distributed and competitive structure where market forces drive the price of electricity and is trying to reduce system operation and maintenance costs under increased competitions.

The electric power wholesale market has being open since 2005 in Japan. Therefore electric power prices are determined by the balance between demand and supply in the market. In the competitive environment, customers request for satisfiable service reliability and lower electricity prices, while generation companies (GENCOS) have to make their own profits. Thus, it is important for generation companies to work out efficient operation plans and maintenance schedules and to maximize their own profit with desirable supply reliability.

The preventive maintenance of thermal generating units is a conventional problem of resource planning in power systems and is formulated as a large scale combinatorial optimization problem. Several methods have been proposed in the literature to solve the maintenance scheduling of generating units. For example, Integer programming (branch and bound) [7], Decomposition method [9], Dynamic programming, Heuristic algorithms and Meta-heuristics algorithms[2] have been applied to the maintenance scheduling

These approaches adopt objectives for equalizing or leveling reserves throughout the planning interval[1], minimizing expected total production costs[1, 2, 9], minimizing variance of un-served energy[8] and leveling the risk of failure to meet demand[10].

However, those studies have not given thought to the price volatility and the profit that is lost by maintenance of generation units in the recent competitive environment. Volatility of electricity prices can increase the uncertainties of profits. Therefore, it is necessary for maintenance scheduling of today to take account of the price volatility as well as the cost of opportunity loss by maintenance.

From these reasons, this paper proposed an improved maintenance scheduling approach by taking account of profits and costs of generation companies in competitive markets where electric power is traded through power exchanges (PX) and electricity prices change day after day.

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For solutions, the proposed combinatorial optimization problem is solved by Reactive Tabu Search (RTS). Additionally, in this maintenance scheduling, the profit of generation companies is maximized keeping desirable supply reliability. This can be achieved by minimizing Opportunity Loss by Maintenance (OLM), which is the expected economic loss when the thermal unit is off line by maintenance and does not sell electricity to the market.

In this proposed maintenance scheduling approach, firstly, the electricity prices at each maintenance period are forecasted using the Neuro-autoregressive model. Secondly, the optimal maintenance scheduling problem is solved by using Reactive Tabu Search based on the forecasted electricity prices. On a test power system, we verify that generation companies are able to maximize their profit by minimizing the proposed objective functions (Opportunity Loss by Maintenance etc.),

2. Profit-based Maintenance Scheduling in Competitive Environment

2.1 Formulation of Maintenance Problem

The aim of the maintenance scheduling is to determine the period in which generating units of an electric generation company should be taken off line for the planned preventive maintenance over the course of three-year planning horizon. In order to make a profit, we propose that the generation company minimizes an objective which is composed of the total Opportunity Loss by Maintenance (OLM) and the Fuel cost (FCOST). The OLM is an economic loss by the maintenance of the generation unit. The Fuel cost is also an indispensable objective, which has been incorporated in several approaches for maintenance scheduling [1, 2, 9]. Moreover, the maintenance cost itself has to be minimized and a constraint on variance of the spinning reserve rate and a number of other constraints should be satisfied.

Objective function

Minimize

$$C = \sum_{j=1}^{N} MC_j + w_1 \sum_{k=1}^{T} f_O(P_k) + w_2 \sum_{k=1}^{T} \left[[M_k][MCP_k] - \sum_{j=1}^{L} f_M\left(P_j\right) \right] + w_3 \sum_{k=1}^{T} Rd_k \tag{1}$$

Constraints

Demand-Supply balance in the system

$$M_k \le P_{MAX} - D_k \tag{2}$$

Lower limit of reserve rate

$$R_k \ge R_{Low} \tag{3}$$

Consecutive periods of maintenance

$$\sum_k x_{jk} = 1$$

and

$$if(x_{jk} = 1), then(x_{jk+1} = x_{jk+2} = \cdots = x_{jk+t_j-1} = 1) \tag{4}$$

Maintenance crew constraints

$$\sum_{j \in dv} x_{jk} \le 1 \tag{5}$$

where,

- MC_j: Maintenance cost for unit j.
- N: The number of thermal units.
- M_k: Total generation capacity under maintenance at period k.
- MCP_k: Market clearing price at period k.
- f_M : Fuel cost function for unit j in maintenance.
- w_k: Weighting coefficient.
- Rd_k: Reserve rate deviation at period k.
- R_{low}: Lower limit of reserve rate.
- R_k: Reserve rate at period k.
- j_{dv} : Set of crew constraint pairs.
- f_{Oj}: Fuel cost coefficient of unit i in operation.
- P_j: Capacity of unit j.
- x_{jk}: State variable of unit; if unit j is in maintenance at period k then x_{jk}=1; otherwise x_{jk}=0.
- j: Number of thermal unit.
- k: Starting period of unit j.
- L: The Number of thermal units in maintenance at period k.
- T: Scheduling term.
- t_j : Required maintenance period for unit j.

2.2 Operation sub-problem

The operation cost is determined by the economic dispatching to minimize the total fuel cost of online generators keeping the balance of supply and demand [16, 17].

The dispatching problem can be expressed as follows.

The objective is to minimize the total fuel cost of thermal plants:

$$FC = Min \sum_{j=1}^{n} (a_j + b_j P_j + c_j P_j^2) \tag{6}$$

subject to inequality constraints on generation outputs

$$P_{\min} \le P_j \le P_{\max} \tag{7}$$

where, a_j, b_j, c_j represent unit cost coefficients of the j-th generator and n is the number of generators connecting to the system in operation.

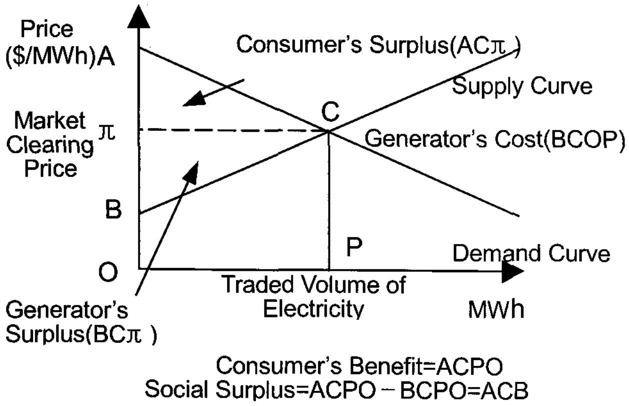

Fig. 1 Social surplus in competitive power markets

3. Market Model and Electricity Price Forecasting

3.1 Market Model

The wholesale electricity market that is called Japan Electric Power Exchange (JEPX) has started in April 2005. JEPX adopts a kind of a uniform price auction and uses the continuous auction scheme in spot markets.

In JEPX, the market clearing price (MCP) is determined according to the principle of the price priority. This principle for MCP settlements is to combine the seller who bids low price and the buyer who bids high price.

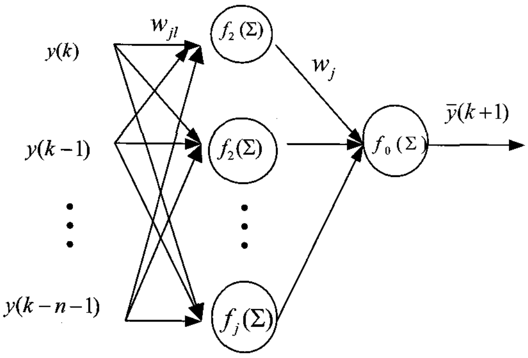

Fig. 2 Three-layered feed-forward artificial neural network

Then the market clearing price at a cross point where supply and demand are balanced is accepted as a contract price of the entire market [15]. In this market auction scheme, the social surplus which is a sum total of consumer's surplus and producer's surplus are maximized to induce an efficient resource allocation. Fig. 1 shows the concept of social surplus [12]. All the buyers will pay the uniform market clearing price which is showed in Fig. 1.

3.2 Demand Forecast Method

In the competitive environment, generation companies must form the strategy to win the competition. Working out efficient maintenance schedules of generation units is a critical task for making their own profit. Since electricity price volatility can increase uncertainties of the profit, it is important for the maintenance scheduling to forecast the electricity prices in advance over the scheduling periods.

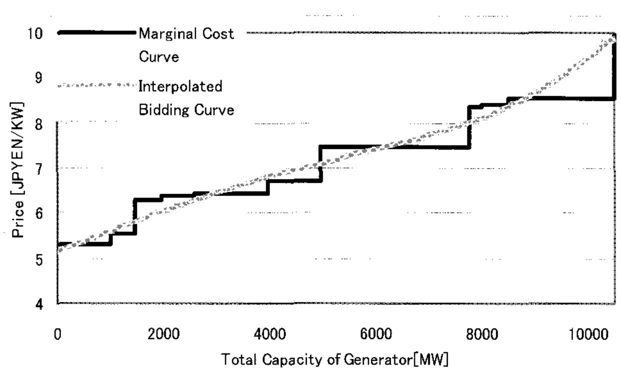

Fig. 3 Marginal prices and an interpolated bidding curve

Electricity price volatility is principally related with changes of demand in the electricity market. Then, the power demand has to be predicted beforehand for forecasting the electricity prices in maintenance scheduling periods. In this paper, the power demand is predicted by a three-layered feed-forward artificial neural network in Fig. 2, The prediction model is constructed and trained by feeding the time series data of the demand and the weather condition and can predict future power demands over several years. Detailed formulations are shown in Appendix.

3.3 Price Forecast Method

In the proposed electricity price forecasting, bidding prices of sellers (power suppliers) are assumed to be determined by marginal prices of their own thermal generation units which are defined as equation (8).

Fig. 3 shows the relation of generation capacities and marginal prices of actual generation units in Japan which are arranged in orders from lower prices to higher prices and also an interpolated bidding curve, which is to use for forecasting electricity prices in the future. This interpolated bidding curve is approximated by the fourth-order function as in equation (9).

By using this bidding curve, future electricity prices can be forecasted according to the total demand of the market in the simplest way. In the application of the method to practical power systems, it is obvious that use of more sophisticated and refined price forecasting approach is needed.

$$MC(P_j) = \frac{d}{dP_j}(FC_j) = b_j + 2c_jP_j \tag{8}$$

$$BC = dP^4 + eP^3 + fP^2 + gP + h \tag{9}$$

where d ,e, f, g, h represent coefficients of the bidding curve function.

4. Optimization Process by Tabu Search

In Tabu Search (TS) optimization algorithm, a number of state transitions in the search space are carried out aiming at finding out the optimal solutions or a range of near optimal solutions. The terminology of Tabu is related to the characteristic that in the optimization process the method avoids revisiting certain areas of the search space that have already been searched [5, 8, 9].

4.1 Advantage of Reactive Tabu Search

It is known that the Tabu search has a shortcoming of being entrapped into a local solution depending on the initial value and Tabu length. In the Reactive Tabu Search (RTS), functions of Reaction and Escape have been incorporated which can expand the search space more and enable us to avoid the loop of search is described in the following [13] and Fig. 4.

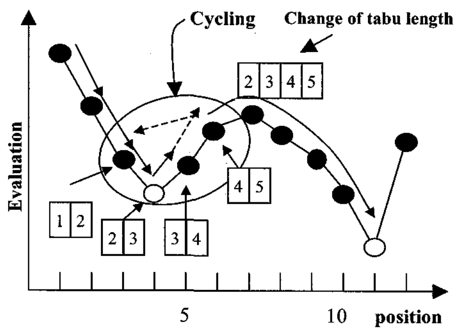

Fig. 4 Expanded functions of reaction in RTS

4.1.1 Reaction Mechanism

As the Tabu length gives influence considerably to the search efficiency in the TS, it is necessary to choose the Tabu length properly in accordance with target problems. However RTS has the function which controls Tabu length automatically as follows;

- Store all solutions which have been visited.
- Extend Tabu length when Current solution has already been searched.
- Shorten Tabu length if solution which has already been searched does not appear for a long term.

4.1.2 Escape Mechanism

In case that the new obtained solution has already been searched, the random search is carried out repetitively and the efficiency of the searches is improved by changing the search space completely.

4.1.3 Reactive Tabu Search

The procedure of RTS can be expressed as follows;

Step.1 Generation of the initial condition
- Generate the initial state and set it as the current state.
- Store the current state into the Tabu list.

Step.2 Generation and evaluation of neighboring states
- Generate all possible neighboring states.
- Check whether the neighboring states are in the Tabu list or not.

Step.3 Selection of the next state
- Move the current state which gives the best objective function value and is not in the Tabu list in neighborhood to the next state.
- Put the current state into the Tabu list.

Step.4 Reaction (Correction of search length)
- Extend Tabu length when Current solution has already been searched.
- Shorten Tabu length if solution which has already been searched doesn't appear for a long term.

Step.5 Escape
- Carried out the Random search if too many configure-tions are repeated too often.

Step.6 Judgment of search termination
- The search is terminated and goes to step2 to search for other solutions, when the number of iterations reaches the prescribed maximum.

4.2 Procedure of Proposed Method

The proposed method is composed of two stages, that is one is for price forecasting and the other is for maintenance scheduling. In the first stage, electricity prices are forecasted using a three layered feed-forward artificial neural network. In the second stage, the maintenance schedule is determined to minimize the objective function given by the equation (1) using RTS. The process of searching neighbor solution for maintenance scheduling in RTS is shown by Fig. 5.

This proposed maintenance scheduling method is formulated as the 0-1 integer-programming problem. Due to this formulation, it becomes easy to check the feasibility and reliability of obtained solutions. Fig. 6 shows the flow chart of this proposed method.

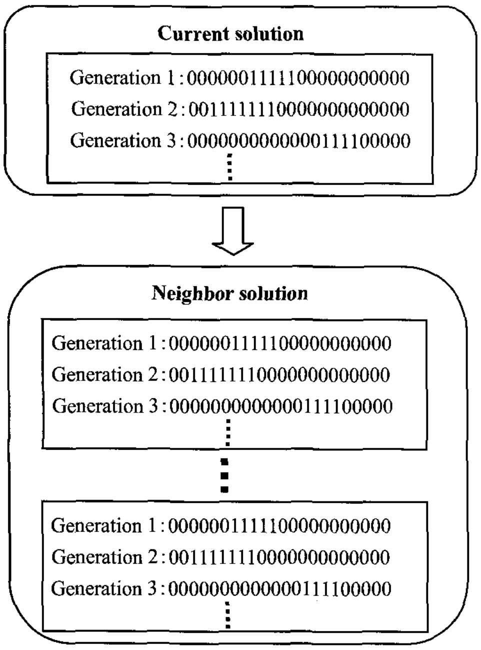

Fig. 5 Searches of neighbors in RTS-based maintenance scheduling

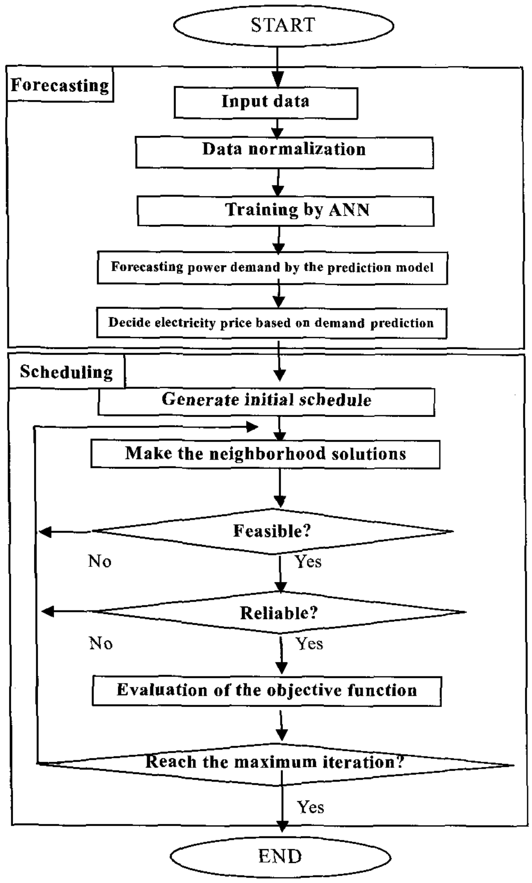

Fig. 6 Flow chart of the proposed method

5. Applications to a Test Power System

The performance of the proposed approach was examined by applying to a test system, which has 26 units in 152 maintenance periods of time (three years) and obtained solutions are compared with those of optimizations under other objective functions, such as minimization of the total reserve rate deviation (TRD), the Opportunity Loss by Maintenance (OLM), and the fuel cost (FCOST) and also minimization of both the fuel cost and Opportunity Loss by Maintenance (FCOST&OLM).

The parameters for each unit of the test system are shown in Table 1. Fig. 7 shows the profile of power demands and forecasted electricity prices for targeted maintenance periods (for three years). It is assumed that the load is increasing by 1% every year and the number of generation units does not change within the maintenance periods

Table 1 Characteristics of each generation unit

Gen. No	Generation Capacity [MW]	Terms for maint. (week)	Gen. No	Generation Capacity [MW]	Terms for maint. (week)
1	1000	14	14	350	8
2	1000	28	15	350	6
3	700	18	16	350	14
4	700	12	17	350	12
5	500	14	18	350	8
6	500	10	19	156	8
7	500	14	20	156	14
8	500	8	21	156	12
9	500	14	22	156	12
10	600	12	23	156	6
11	350	12	24	156	12
12	350	8	25	125	8
13	350	12	26	125	6

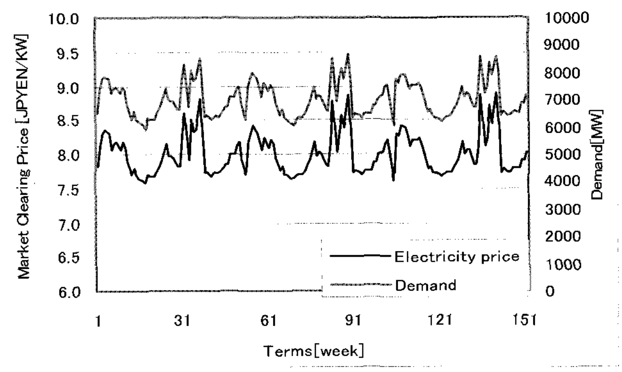

Fig. 7 Changes of demand and forecasted electricity prices

Fig. 8 shows the maintenance scheduling reserve rate obtained under each objective function. Table 2 illustrates the maximum, minimum and average reserve rates of each case.

Table 2 shows the comparison of optimized solutions under TRD, FCOST, OLM and both FCOST and OLM. The average reserve rates and maximum reserve rates obtained under different objective functions are almost equal. On the other hand, it shows that the minimum reserve rates obtained under OLM and OLM&FCOST are 9% and 10% respectively which are smaller than those obtained under other objective functions. The reason why the minimum reserve rates obtained under OLM and OLM&FCOST are smaller than others is that by introducing OLM for optimization, most of generator maintenances are carried out when the market clearing price (MCP) is low. However, the obtained reserve rate (9%) is sufficient to satisfy the requested supply reliability through the targeted periods.

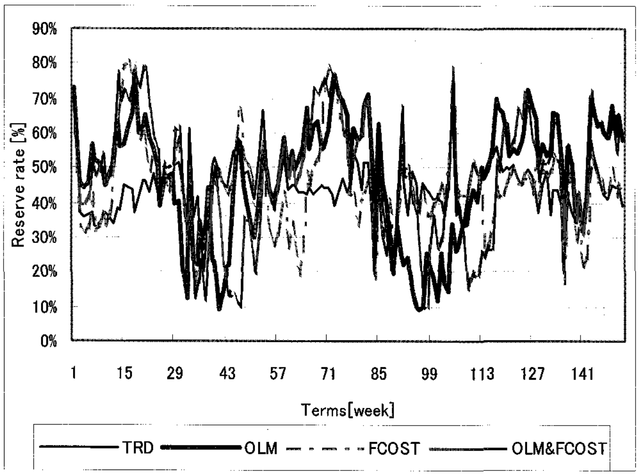

Fig. 8 Reserve rates obtained under both OLM and ARR

Table 2 Comparison of reserve rates under different objecttives

	TRD	OLM	FCOST	OLM&FCOST
Minimum	19%	9%	17%	10%
Maximum	73%	78%	80%	78%
Average rate	44%	47%	45%	47%

Table 3 represents the fuel cost and the opportunity loss by maintenance and total cost under each objective function(each study case). Table 4 shows the ratio of each study case and comparisons with the ratio under TRD. In this table, the largest ratio obtained under TRD is set to be 100% for comparison. It shows that FCOST &OLM gives the lowest total cost and therefore the proposed method is superior to the others in maintenance cost reductions. From Table 3 and Table 4, we can see that by the proposed objective function, OLM&FCOST, we can decrease the total cost mostly. Concretely, under OLM&FCOST, the total cost of maintenance can be decreased by 4 % and it is about 158 million [JPYEN] lower than that obtained under TRD.

Table 3 Comparison of costs under different objectives

	Fuel cost	OLM cost	Total cost
TRD	3,554	908	4462
OLM	3,630	734	4364
FCOST	3,498	868	4366
OLM&FCOST	3,548	756	4304

unit is million JPYEN.

Table 4 Comparison of costs under different objectives

	Fuel cost	OLM cost	Total cost
TRD	100%	100%	100%
OLM	102%	81%	98%
FCOST	98%	96%	98%
OLM&FCOST	100%	83%	96%

These results show that the proposed method has minimized the opportunity loss by maintenance and fuel costs simultaneously with keeping the sufficient supply reliability. If viewed from a different angle, the proposed maintenance scheduling leads to increase of the profit for GENCOS.

6. Conclusion

This paper proposed a new profit and cost based-maintenance scheduling by making use of Reactive Tabu search (RTS) in the competitive environment.

This maintenance scheduling approach introduced a novel objective function; OLM to give consideration to electricity volatilities in the electricity market. Firstly, the electricity prices were forecasted at each maintenance period using the three-layered feed-forward artificial neural network and the interpolated bidding curve. Secondly, the maintenance scheduling was formulated as a combinatorial optimization problem and was solved by using Reactive Tabu Search based on the forecasted electricity prices.

The proposed approach was applied to a practical thermal plant maintenance scheduling having 26 units over 152 maintenance periods and the application results have shown that the approach is effective and applicable to actual maintenance scheduling and makes generation companies profitable.

Appendix

The multi-layer perception (MLP) neural network is applied to determine parameters for an autoregressive (AR) model considering n discrete time periods below.

$$\hat{y}(k+1) = a_1 y(k) + a_2 y(k-1) + \cdots + a_n y(k-n+1) \qquad \text{(A1)}$$

where $y(k)$ is a time series datum observed.

A three layer MLP neural network, as shown in Fig. 2, is introduced to obtain the AR model. All activation functions in hidden layer are *tanh*(x) (described as f_j in Fig. 2), and the activation function in the output layer is $x(F_0(\Sigma) = \sum_{j=1}^{n_h}(x) + w_0)$.

The output of the MLP is

$$\tilde{y}(k+1) = \sum_{j=1}^{n_h} w_j \tanh\left[\sum_{l=1}^{n} w_{jl}\varphi(l) + w_{j0}\right] + w_0 \qquad \text{(A2)}$$

where

$$\varphi(l) = y(k-l+1),\ l = 1,2,\ldots,n$$

w_{jl} : Weight which connects input and hidden layer

w_j : Weight which connects output and hidden layer

n_h : Number of hidden neurons

w_{j0} : weight which connects hidden layer and bias

w_0 : Weight which connects output layer and bias

W^0 : Vector form of w_j, $[w_1, w_2, \ldots, w_{nh}]$

W_l^I : Vector form of w_{jl}, $[w_{1l}, w_{2l}, \ldots, w_{nhl}]$

The derivative of the output with respect to the input φ_l is

$$\frac{\partial \tilde{y}(k+1)}{\partial \varphi(l)} = \sum_{j=1}^{n_h} w_j w_{jl}\left(1 - \tanh^2\left[\sum_{l=1}^{n} w_{jl}\cdot\varphi(l) + w_{j0}\right]\right) \qquad \text{(A3)}$$

Now, to make the model much simpler, linear activation function for f_j and F_0 is applied to the MLP in Fig. 2, and the linear output can be represented as follows:

$$\hat{y}(k+1) = \sum_{j=1}^{n_h} w_j\left[\sum_{l=1}^{n} w_{jl}\cdot\varphi(l) + w_{j0}\right] + w_0 \qquad \text{(A4)}$$

and the derivative of the output with respect to the input $\varphi(l)$ is

$$\frac{\partial \hat{y}(k+1)}{\partial \varphi(l)} = \sum_{j=1}^{n_h} w_j w_{jl} = W^0 W_l^I \qquad \text{(A5)}$$

From Taylor series expansion, parameter a_1 is obtained by

$$a_1 = \frac{\partial \hat{y}(k+1)}{\partial y(k)} = \frac{\partial y(k+1)}{\partial \varphi(1)} = W^0 W_1^I \qquad \text{(A6)}$$

In general, the parameters of the AR model (A1) can be obtained as follows:

$$\left[a_1, a_2, \ldots, a_n\right] = \left[W^0 W_1^I, W^0 W_2^I, \ldots, W^0 W_n^I\right] \qquad \text{(A7)}$$

From (A1) and (A7), the vector of the most likely demand (crisp value) can be obtained.

For the linear activation function in the neural network the inputs are scaled between 0.1 and 0.9 by the maximum and minimum inputs of the time window considered below

$$y'(k-l+1) = s\cdot y(k-l+1) + b \qquad \text{(A8)}$$

where

$$s = \frac{0.8}{y^{\max} - y^{\min}}$$

and

$$b = \frac{0.1y^{\max} - 0.9y^{\min}}{y^{\max} - y^{\min}}$$

where

$$y^{\max} = \underset{l}{Max}[y(k-l+1)]$$

$$y^{\min} = \underset{l}{Min}[y(k-l+1)]$$

and

$$l = 1,2,\ldots,n$$

Because the time window for the training moves step by step, $y^{\max}$ and $y^{\min}$ are subsequently updated for a correct scaling. Outside this window there is no need of assuming normal distribution of errors, which can give rise to the difficulty of stationary in regular regression-based time series modeling.

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