Applying Neural Networks to the Extraction of Available Investment Information from the Previous Day's Stock Market*

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Abstract

The present paper aims to assess the performance of ANN(Artifical Neural Networks) prediction for short term stock tradings, from the viewpoint of Candle chart technicians. A methodologically different nonlinear model will be compared with ANN. This paper will clarify the possibility of Candle techicians to extract the available information from the previous day, especially with ANN.

Key words: *Artifical Neural Network (ANN), Back Propagation, Technical analysis, Candle chart, BDS test.*

1 Introduction

A number of empirical studies have constructed ex ante forecasting models for stock returns (see e.g., the articles of [6], [8]). Most of these studies have set their targets on predictions for long-term stock investment. In recent years, however, short-term investments have also taken on importance in stock markets as IT technology has developed and market information has come to be obtained easily.

Assuming that we are day-traders who aim at capital gain for short-term trading on stocks and bonds, what type of analytical tools should we use for our investments? Market traders, including day-traders, often use technical analyses (e.g., Moving Average, Point and Figure, and Elliot Wave) for their predictions. The traders who are fond of technical analyses are often called technicians. They display special figures which are composed of market prices at multiple time periods on the chart, and they make strategies for capital gain. A Candle chart is one of the most popular analyses amongst these, and is composed of Candles having daily stock prices (open price, high price, low price, closing price)[1)]. (See an example of a Candle chart in Figure 1.) Many Candle technicians think that these 4 prices are the most important prices to symbolize the day's market and that Candles represent the daily stock market without the market noise. These technicians think that an intra-day's Candle has information available for market predictions for the next day and apply Candle chart to market predictions in various ways[2)]. Can we extract available investment information from the previous day's Candle bar?

It seems quite difficult for us who are not technicians to predict market movements only with Candles. Therefore this paper presumes the Candle technician who acts rationally, does as follows:

(1) He checks the intra-day's market movement and extracts the open price, high price, low price, and closing price, and

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1) By contrast Bar chart is composed of 3 prices, viz. high price, low price, and closing price.

2) The technical analysis called Sakata-Goho, which analyzes Candle chart, is famous and used by a wide range of traders in Japanese stock markets.

draws a Candle bar for each day.

(2) He predicts the next day's closing price based on (1)'s Candle.

(3) He learns the gap between his predicted value and the real one, learns his failure point, and tries to minimize his failure.

(4) He repeats (1) to (3), and creates his own strategy to predict the next day's closing price.

The problem is how the Candle technician acts rationally with his markets. If the Candle technician intends to do so, he certainly needs some tools to rationalize his behavior. This paper presumes such Candle technicians employ ANN (Artifical Neural Network) technology, which emulates the human learning process. ANN is a trainable analytical tool for pattern recognition problems, and has been applied in a variety of fields, including the financial research area. (See e.g., the article of [5].) The purpose of this paper is to assess the performance of ANN (Artifical Neural Networks) prediction for short-term stock tradings, from the view point of Candle chart technicians.

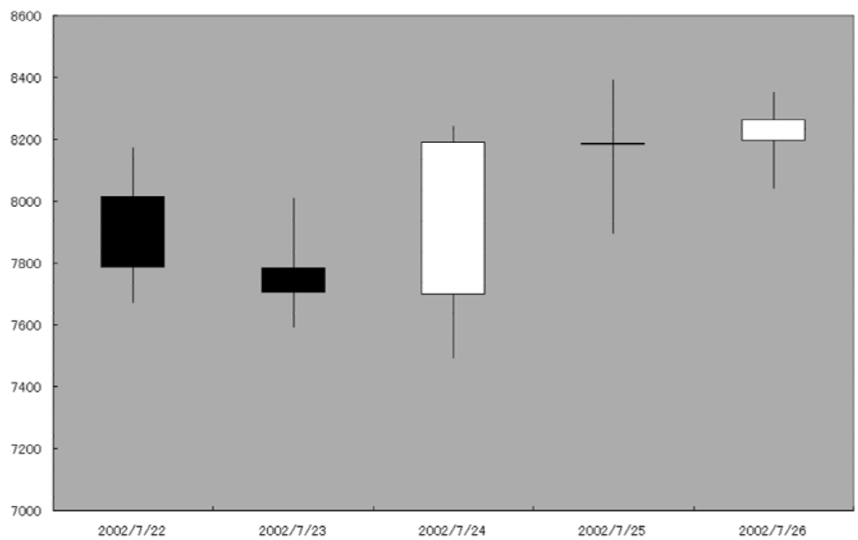

Figure 1 An Example of a Daily Candle Chart (Dow Jones Average 2002/7/22–2002/7/26)

2 Experimental

2.1 Model

As referred to in the previous section, the present paper assumes that the Candle technician acts rationally for the purpose of trading profits. Under this assumption, this paper has adopted the ANN approach and the standard Back Propagation algorithm for learning rules against markets.

The assumptions of this article, which uses Back Propagation algorithm, can be summarized as follows:

- ANN in this article has 3 layers, viz.input layer, hidden layer, and output layer. Each layer has several units[3].
- Let the ith unit of input layer be U_i, the jth unit of input layer be U_j, and the kth unit of input layer be U_k.
- Let the interconnection weight between U_i and U_j be Ω_{ij}, the interconnection weight between U_j and U_k be Ω_{jk}.
- χ is defined as the set of learning pattern, and χ_s is defined as the set of learning patterns which belongs to the class Ψ_s (s = 1, 2,…, n).

3) The feature of these layers is threshold logic unit which unites weighted sum with threshold function.

The network is assumed to be input as a learning pattern x_q ($x \in \Psi_s$, $\exists q \in s$) Let the output from U_i be ϕ_{iq} and the input into U_j be ψ_{jq}. Then,

$$\psi_{jq} = \sum_i \Omega_{ij} \phi_{iq}. \tag{2.1}$$

Let the output from U_j be ϕ_{jq}, and $F_j(\ )$ be a nonlinear function. It is usually defined as a Sigmoid function. Then,

$$\phi_{jq} = F_j(\psi_{jq}) = \frac{2}{1 + exp(-\sum_i \Omega_{ij}\phi_{iq} - Z_j)} - 1. \tag{2.2}$$

Z_j is the threshold of U_j. In the same way, let the input into U_k be ψ_{kq}, the output from U_k be ϕ_{kq}, and $F_k(\ )$ be as Sigmoid function, and Z_k be the threshold of U_k. Then,

$$\psi_{kq} = \sum_j \Omega_{ij} \phi_{jq}. \tag{2.3}$$

$$\phi_{kq} = F_k(\psi_{kq}) = \frac{2}{1 + exp(-\sum_j \Omega_{jk}\phi_{jq} - Z_k)} - 1. \tag{2.4}$$

Let the teacher's signal of U_k against q be Θ_{kq} and which gives the squared mean error ε_q;

$$\varepsilon_q = \frac{1}{2}\sum_k (\phi_{kq} - \Theta_{kq})^2. \tag{2.5}$$

Back Propagation minimizes ε_q by a learning process. According to the steepest descend method, Ω_{ij} will be modified into $\acute{\Omega}_{ij}$. That is,

$$\acute{\Omega}_{ij} = \Omega_{ij} - \rho \frac{\partial \varepsilon_q}{\partial \Omega_{ij}}. \tag{2.6}$$

where ρ is a positive constant. As U_j is in the hidden layer, this is rewritten as:

$$\acute{\Omega}_{ij} = \Omega_{ij} - \rho \sum_k \frac{\partial \varepsilon_q}{\partial \psi_{kq}} \Omega_{jk} \phi_{jq}(1 - \phi_{jq}) \phi_{iq}. \tag{2.7}$$

(See Proof; Appendix A.)

2.2 Data

This article selected NASDAQ daily return rates (for open price, high price, low price, and closing price) for the years 2000, 2001 as data. These were separated into those of (1)(the first business day of January to the the last business day of November) and (2) (the first business day to the the last business day of December). (1) is used as learning data and (2) will be compared with the ANN prediction. The statistical summary of closing prices of (1) are shown in Table 1.

2.3 Tests for Nonlinearity

The ANN approach deserves more careful attention. As ANN is a typical nonlinear model, the nonlinearity of a time series should be tested with priority. This article adopts Runs test and BDS test for nonlinearity tests. In case the nonlinearity of the time series is denied, it is needless to say that we should predict markets in the Candle techinician's way, not with ANN, but with some linear models. By contrast, in the case in which the time series has nonlinearity, we may think that we might use nonlinear models, including ANN model, for market prediction. The result of Runs tests is shown in Table 2. According to the result of Table 2, NASDAQ daily return rates (for open price, high price, low price, closing price) seemed to have linearity rather than non-linearity.

Table 1 Summary of closing price (return rate of NASDAQ)

2000 Jan-Nov				
	Mean	**Std.**	**Min.**	**Max.**
	−0.00087205	0.012834033	−0.044160847	0.033167885
	Skewness	**Kurtosis**		
	−0.014449882	3.270562299		
2001 Jan-Nov				
	Mean	**Std.**	**Min.**	**Max.**
	−0.000375978	0.027685681	−0.068320966	0.141732043
	Skewness	**Kurtosis**		
	0.661247289	5.742771088		

We should be more careful of applying time series, however, with a methodologically different nonlinear test. BDS test is an excellent test which is verified for nonlinearity of time series. The framework of BDS test is based on the calculation method of correlation dimensions. (See [1] [2] [3].) BDS statistics are the normalized statistics which are asymptotically distributed normally with zero mean and unit variance.The maximum dimension (m) is set to 4, and the epsilon parameter ($\bar{\varepsilon}$) is set to a fraction of the standard deviation of the time series, and the half of a fraction of the standard deviation of the time series.

The result of BDS tests is shown in Table 3. BDS tests rejected the null hypothesis in most cases. The result indicated that BDS tests showed positive results for nonlinearity of the NASDAQ market in both the years of 2000 and 2001.

Table 2 Runs tests

	open	**high**	**low**	**close**
2000 Jan-Nov Z-value	1.648783326	0.066225365	−3.890169382	−1.516332507
2001 Jan-Nov Z-value	0.332897842	−0.864479423	−2.194898605	−0.598395586

Table 3 BDS tests

	$m=2$ $\bar{\varepsilon}=\sigma$	$\bar{\varepsilon}=\sigma/2$	$m=3$ $\bar{\varepsilon}=\sigma$	$\bar{\varepsilon}=\sigma/2$	$m=4$ $\bar{\varepsilon}=\sigma$	$\bar{\varepsilon}=\sigma/2$
2000 Jan-Nov (open)	11.293544	5.817636	−2.999833	−1.85376	−1.145561	−0.380509
(high)	6.6474579	19.025469	−4.159104	−1.995687	−1.860356	−0.701291
(low)	6.796680	−9.721227	−7.479251	−2.591253	−3.468289	−0.924028
(close)	−10.577516	−6.59319	−2.778609	−1.230418	−1.011074	−0.325085
2001 Jan-Nov (open)	− 4.977204	−5.832769	−2.996008	−1.274859	−1.179876	−0.389616
(high)	10.856733	−9.748214	62.46617	−2.701681	−2.269118	−0.970211
(low)	1.230908	3.376807	−3.699550	−1.831648	−1.442260	−0.544756
(close)	9.810146	−4.493813	−7.463559	−3.373148	−3.300926	−1.180466

2.4 Operations

According to the result in the previous subsection, if a Candle technician tries to act rationally, his prediction for markets should be conducted with nonlinear models. First of all, this article adopted ANN for such for his market predictions. The ANN operations of this article are shown in Table 4. As referred to in this section, the ANN of this article was the standard one which had 1 input layer, 1 hidden layer, and 1 output layer. The input layer had 4 nodes and the output layer had 1 node[4]. That is, the 1st business day's each 4 prices (open price, high price, low price, and closing price) were set to 4 nodes accordingly, and the 2nd business day's closing price was set to the output layer. The ANN learns the connection between the input nodes and the output node via the Back Propagation method. This learning procedure was repeated from the 1st business day of January to the last business day of November of the corresponding year. And with the accomplished topology through the learning process, this article made predictions for the corresponding December.

Table 4　Operations

Method		Back Propagation
		Training only
Function		Binary sigmoid function
Numbers of nodes	input layer	4
	hidden layer	2
	output layer	1

3 Results and discussion

3.1 Results

The results of the previous section's learning procedure are shown from Table 5 to Table 10. With this attained topology, ANN predicted the closing price of the corresponding December.

(See Figure 2 and Figure 3.)

The Prediction showed a good performance. Although the quality of the prediction might be rough, it is due to the reason that this analysis streamlined the network's learning period to a minimum for the purpose of short term research. Therefore ANN predictions might be formed accurately with more learning time. These results will clarify the claim that the previous day's intra-day market movement has highly available information for the next day's market prediction. Therefore the strategy of the Candle technician to extract the information for market prediction can be stated as a rational one. In addition, ANN has the possibility of making good use of the information provided in the Candle bar.

From these results, especially, the ANN seemed to capture the volatility of markets. This phenomenon will be discussed in the next subsection.

Table 5　Connection Weights from Input Nodes to Hidden Nodes (2000 Jan-Nov)

		Input Node			
		1	**2**	**3**	**4**
Hidden Node	1	0.168015	0.816452	−0.512622	−0.030915
	2	0.232948	−0.308044	0.866237	−0.460631

4) This article sat 2 nodes in the hidden layer so that this ANN could be composed of shaped triangles.

Table 6 Connection Weights from Hidden Nodes to Output Nodes (2000 Jan-Nov)

	Hidden Node	
	1	**2**
Output Node	0.40673	−0.065647

Table 7 Bias for Each Node (2000 Jan-Nov)

		bias
Hidden Node	1	−0.821948
	2	−0.364048
Output Node	1	−0.180921

Table 8 Connection Weights from Input Nodes to Hidden Nodes (2001 Jan-Nov)

		Input Node			
		1	**2**	**3**	**4**
Hidden Node	1	0.318467	0.925074	−0.488453	0.558146
	2	0.078875	−0.4134	0.847834	−0.978608

Table 9 Connection Weights from Hidden Nodes to Output Nodes (2001 Jan-Nov)

	Hidden Node	
	1	**2**
Output Node	0.783301	−0.928168

Table 10 Bias for Each Node (2001 Jan-Nov)

		bias
Hidden Node	1	−0.786511
	2	−0.245366
Output Node	1	−0.465269

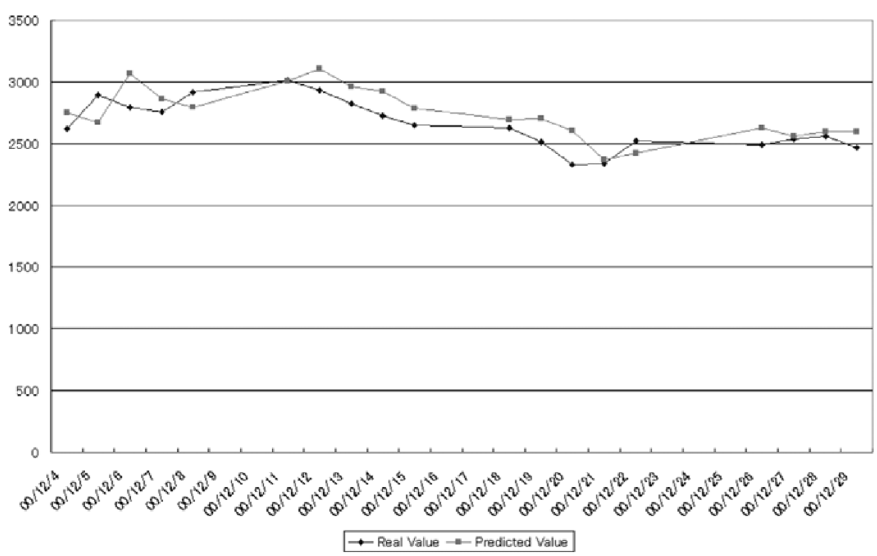

Figure 2 ANN Prediction for December 2000

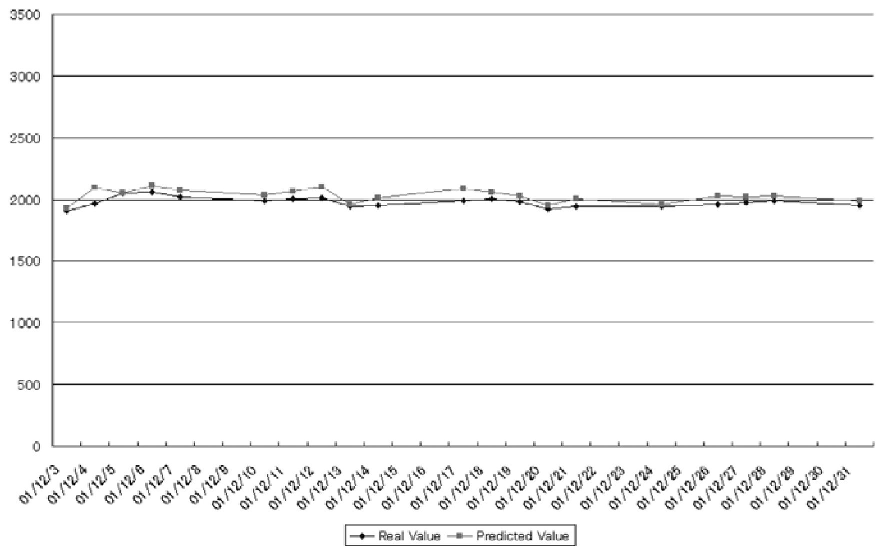

Figure 3 ANN Prediction for December 2001

3.2 Comparison and Discussion

As stated in the previous subsection, ANN seems to provide reasonable predictions to some extent. The performance of ANN analysis needs to be carefully judged, because there is a possibility that other nonlinear regression models are more useful using a Candle technician's mindset. Many articles have studied this area using such comparisons. (See e.g., the articles [4] and [7].) As stated in the first section, however, these studies have long-term investment standpoints whose targets are different from that of this article.

This article adopted the standard nonlinear (NL) regression model as follows:

$$y_t = \sum_{i=1}^{4} e^{\alpha_i X_{it}} + \beta + \varepsilon_t. \tag{3.1}$$

X_{1t} : the business day's open price,

X_{2t} : the business day's high price,

X_{3t} : the business day's low price,

X_{4t} : the business day's closing price,

y_t : the next business day's closing price.

The result of this NL regression is shown in Table 11.

Table 11 Nonlinear Regression

		Parameters				
Year	**Summary**	α_1	α_2	α_3	α_4	β
2000Jan-Nov	Esimate	−0.372928	0.314922	−0.0153767	−0.0810818	−4.00611
	Std. Error	0.206215	0.231077	0.154335	0.160277	0.00448934
	t-value	−1.80844	1.36285	−0.0996325	−0.505885	−892.362
2001Jan-Nov	Esimate	−0.22254	0.274428	0.25377	−0.194454	−4.00113
	Std. Error	0.232468	0.200778	0.213994	0.177552	0.00413921
	t-value	−0.957291	1.36683	1.18587	−1.09519	−966.641

Residual standard error: (2000Jan-Nov) 0.0293135, (2001Jan-Nov) 0.0261009

This article also predicted December's closing price in the same way as in the previous subsection with a NL model equipped with these parameters. The Performance of the NL prediction seems to be better than that of ANN from the standpoint of RMSE[5]. The RMSEs of NL predictions were less than those of ANN. In spite of these results, this article can conclude that ANN predictions are superior to NL predictions, because the ANN will capture the dynamics of markets.

(See Figures 4 and 5. These figures show the density plots of ANN predictions and NL predictions, and real values. The axis of the ordinate indicates the density and the axis of the abscissa indicates the return rate.)

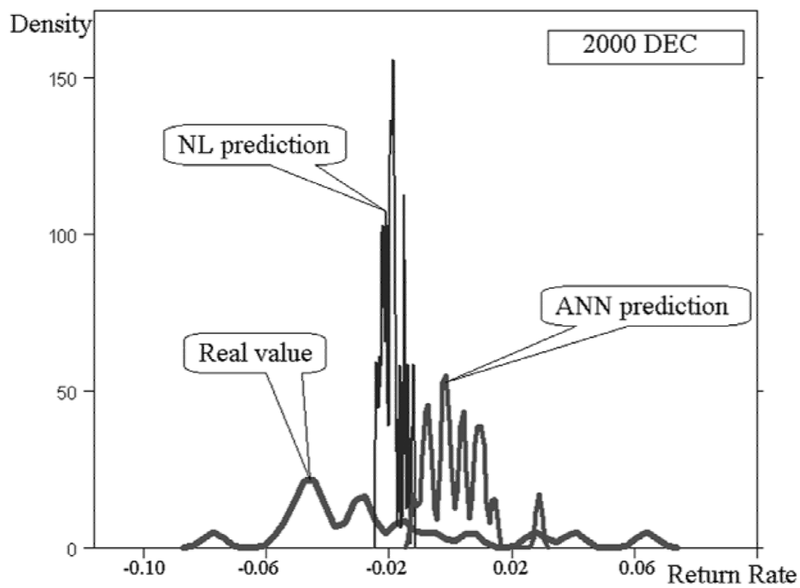

Figure 4　Comparison for December 2000

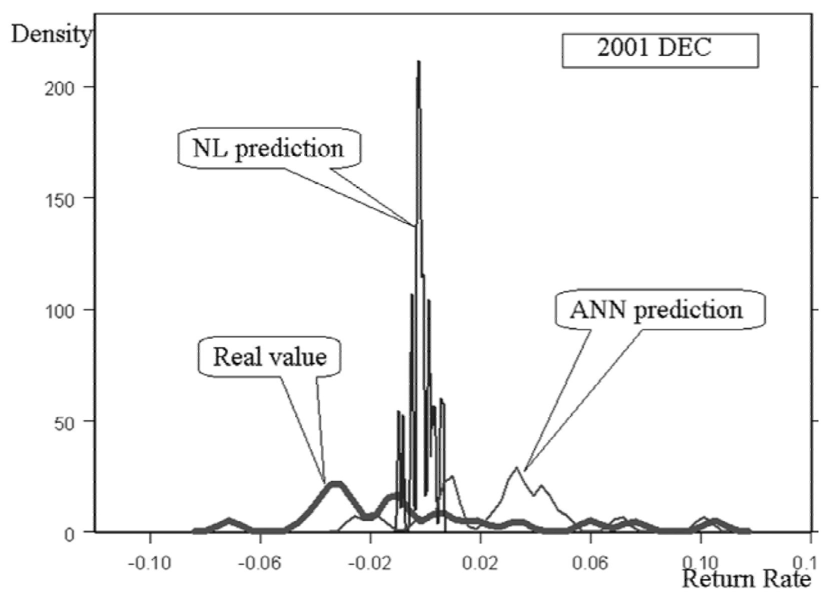

Figure 5　Comparison for December 2001

5） RMSE is the root mean squared error between the actual return rate and predicted return rate.

4 Conclusion

In the present paper, intra-day 4 prices have been used to extract available investment information from the previous day's market. The analysis has been carried out with an ANN application and also a methodologically different model in order to compare the performance of the model. Even with the highly limited data used in this paper for ANN learning, this article achieved the result that ANN showed significant results for predicting the next day's closing price. Under the condition in which ANN is used, a technical trader who uses Candle chart for market prediction will have the possibility of beating the market.

Despite the positive ANN prediction results obtained, another study should be conducted using another ANN model. The profound aspects of the feelings of technical traders should also be considered carefully (e.g., psychological factor of whether the figure color is white or black in Candle chart). As mentioned above, future research study should test the result of this article with a method of actual pattern recognition. In this study, the available information will be extracted from the unvarnished Candle chart.

Appendix

A Proof.

The correction method of interconnection weights between U_i and U_j is written as:

$$\begin{aligned}
\acute{\Omega}_{ij} &= \Omega_{ij} - \rho\frac{\partial \varepsilon_q}{\partial \Omega_{ij}} && \text{(A.1)}\\
&= \Omega_{ij} - \rho\frac{\partial \varepsilon_q}{\partial \psi_{jq}}\frac{\partial \psi_{jq}}{\partial \Omega_{ij}} && \text{(A.2)}\\
&= \Omega_{ij} - \rho\frac{\partial \varepsilon_q}{\partial \psi_{jq}}\phi_{iq}. && \text{(A.3)}
\end{aligned}$$

Especially,

$$\begin{aligned}
\frac{\partial \varepsilon_q}{\partial \psi_{jq}} &= \frac{\partial \varepsilon_q}{\partial \phi_{jq}}\frac{\partial \phi_{jq}}{\partial \psi_{jq}} && \text{(A.4)}\\
&= \frac{\partial \varepsilon_q}{\partial \phi_{jq}}F'_j(\psi_{jq}) && \text{(A.5)}\\
&= \sum_k \frac{\partial \varepsilon_q}{\partial \psi_{kq}}\frac{\partial \psi_{kq}}{\partial \phi_{jq}}F'_j(\psi_{jq}) && \text{(A.6)}\\
&= \sum_k \frac{\partial \varepsilon_q}{\partial \psi_{kq}}\Omega_{jk}\phi_{jq}(1-\phi_{jq}). && \text{(A.7)}
\end{aligned}$$

By (A.1) and (A.3), we can get the following equation as the correction way of interconnection weights.

$$\acute{\Omega}_{ij} = \Omega_{ij} - \rho\sum_k \frac{\partial \varepsilon_q}{\partial \psi_{kq}}\Omega_{jk}\phi_{jq}(1-\phi_{jq})\phi_{iq}. \tag{A.8}$$

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