An Intelligent Trend Prediction and Reversal Recognition System Using Dual-module Neural Networks

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Abstract

Short-term trends of price movement for common stocks traded on the Taiwan stock market have been modelled and predicted using the dual-module neural networks (dual net) proposed in this paper. Both neural network modules of the dual net learn the correlations between the trends of price movement and the retrospective technical indices. An adaptive reversal recognition mechanism which can self-tune the threshold to identify the buying or selling signals is developed in our system. Due to the features of acceptable returns, high hit ratio and low risks shown in the performance evaluation, an intelligent stock trend prediction and reversal recognition system can be realized using the dual-module neural networks.

1 Introduction

The modelling capability of neural networks has been widely applied to forecasting, adaptive control, pattern recognition and signal processing [1-5]. Unlike traditional expert systems where knowledge is represented explicitly in the form of rules, neural networks can learn from examples. This means that neural networks can represent, model, or predict the behavior of known systems without being given any rule or model in advance. In addition, the inherent parallelism of neural networks allows fast parallel searches and best-match computations, thereby alleviating much of the computational overhead involved when applying traditional modelling techniques to complex systems.

On the Taiwan stock market, most dealings are stimulated for chasing the short-term price fluctuations. This short-term characteristic of trading inspires the development of trend prediction systems which can forecast the short-term trends of price movement. Although the Random Walk Theory claims that price changes are serially independent and that price history is not a reliable indicator of future price trends. The fact that previous researchers have not been able to discover the presence of suitable models does not prove they do not exist. In this paper, we will show that the inherent relationships between the retrospective technical indices and the future trends of short-term price movements can be exploited using the *dual net* architecture. A fast learning algorithm with adaptive learning speed control is used for filtering well-trained patterns out to eliminate redundant back-propagations. On tracking the short-term trends of price movement for trained patterns, the *dual net* can fit the real trends to a near optimal accuracy of 99%. And the trend prediction for patterns not been trained by the *dual net* can track the real behavior of the market with an acceptable accuracy.

Based on the statistical relationships between the predictive output of the *dual net* and the timing of impending short-term effective reversal patterns (ERPs), we created an adaptive recognition mechanism which can self-tune its threshold to indicate the buying or selling signals according to the weighted sum of paired outputs from the *dual net*.

According to the results of the performance evaluation simulating the real market, our *dual net* and reversal recognition mechanism, guarantee low risk and high return for an intelligent and self-adaptive trend prediction and reversal recognition system that indicates near-optimal timing for buying or selling stocks on the Taiwan stock market.

2 Stock data analysis

2.1 Traditional stock data analysis

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In a typical free market, trading is stimulated by the market moving prices up to tempt the sellers or moving prices low enough to attract the buyers. This price fluctuation thus behaves as a goad for promoting opportunities. The market as a result tries to establish an equilibrium between buying and selling forces. This dynamic mechanism of trading has inspired traders to predict the future trends of the market. Two kinds of analytical approaches are taken [9]:

(1) Fundamental analysis. Forecasting is based on macro economic data such as exports and imports, money supply, interest rates, foreign exchange rates, inflationary rates, and unemployment figures, etc.. The basic financial status of companies is also taken into consideration.

(2) Technical analysis. Predictions are made by exploiting implications hidden in past trading activities by analyzing patterns and trends shown on the price and volume charts. Predictions are based on the rationale that history will repeat itself and that the correlation between price and volume reveals market behavior. This micro-level scrutiny does not take any external influential factors, like news about wars in the Middle East, into consideration.

2.2 Stock data modelling on the *dual net*

We established the stock data model on the *dual net* from technical analysts' point of view. There are two arguments supporting this technical approach. First of all, short-term trends of price movement, the subject of the predictive model, are considered to be dependent on the emergent news affecting the market or the difference between the buying and selling forces on the market. Although the efficient market hypothesis holds that prices fluctuate randomly about their intrinsic value, and it also holds that the best market strategy to follow would be a simple "buy and hold" strategy as opposed to any attempt to "beat the market", the fact that the intrinsic value for a stock is not fixed forever encourages us to find a model which can "beat the market". We believe that once the intrinsic value of a stock is shifted due to changes made on some macro economic factors, the only way for the market to compensate the discrepancy between the market price and the new intrinsic value of that stock is either to pull up or to push down the market price via dealings through the market. And there would be clews on the price and volume charts significant enough for the neural networks to built a computational model which can correlate the short-term trends of price movement with the retrospective technical indices. Secondly, an extensive computation and a long training period are needed for an expert to build the technical views of the market. Even well trained investors can't easily predict the impending market movement from several charts and figures for each stock, not to mention that there are hundreds even thousands of different stocks on the stock market. By reason of being difficult to examine the news quantitatively by the computer itself, we decided to equip the computer only with technical views of the stock market.

To build the correlation between the predictive short-term trends of price movement and the retrospective technical indices, the *dual net* has been trained by special training patterns. The input vector, the selected set of technical indices, extracts the retrospective features of the selected stock. The output vector, on the other hand, models the predictive short-term trends of price movement of the chosen stock. The discussion of retrospective input vector and predictive output vector are presented in the following two sections.

All technical indices of stock data are represented in the form of bias or oscillator. A bias is the ratio of the difference between a specific technical index and its moving average divided by that moving average. An oscillator is the bias of short-term moving average relative to long-term moving average. Both of bias and oscillator help to free the technical indices of the selected stocks from the dependence on the absolute levels and the binding on specific trading days.

2.3 Retrospective feature extraction

The simplest way of establishing a technical view of the stock market is to use only raw data on time series. The technical view of a stock for the n-th trading day can be defined as a 5-tuple $S_n = (D_n, H_n, L_n, C_n, V_n)$, where

D_n is the n-th trading day,

H_n is the highest price during the n-th trading day,

L_n is the lowest price during the n-th trading day,

C_n is the closing price for the n-th trading day, and

V_n is the daily trading volume for the n-th trading day.

Although $S_N = \{S_n \mid n = N-1, ..., 1, 0\}$ is usually viewed as the retrospective characteristic of a stock for the latest N trading days, this simple model suffers from its dependence on time and its representation in pure levels. In order to extract temporal context from S_N, a transformation is needed to figure out rates of changes from temporal price fluctuation between levels. It is also believed that a time-invariant system is easier to model than time-variant ones. So we developed a transformation T: $S_N \rightarrow R_N$ which can extract retrospective features from the raw time-dependent 5-tuple data set to form a time-invariant 16-tuple[1] one. Keeping the retrospective characteristics of a stock spanned by the sixteen-dimension space R_N, T eliminates the time dependent and level sensitive problems by adapting biases and oscillators rather than raw levels and moving averages. This 16-tuple is composed of sixteen technical indices which are chosen from thirty candidates. We use the order of each candidate's inclusion in the stepwise selection process of the SPSS^X multiple linear regression analysis as the major selection criterion [10].

The projection of stock market data on each axis of R_N is generated by the following equations. Four equations are used as atomic operations to generate other technical indices. The general infinite impulse response transformations are defined in equation (2.1) to equation (2.3) to calculate the moving average, the bias and the oscillator for a specific time series data X_n. Equation (2.4) denotes the relative ratio of difference for X_n between two consecutive trading days.

$$MA_k(X_n) = \frac{1}{k}(X_n) + \frac{k-1}{k} MA_k(X_{n-1}) \tag{2.1}$$

$$X_n[k\_Bias] = [X_n - MA_k(X_n)] / MA_k(X_n) \tag{2.2}$$

$$X_n[j\_k\_Osc] = [MA_j(X_n) - MA_k(X_n)] / MA_k(X_n) \tag{2.3}$$

$$X_n[Variance] = (X_n - X_{n-1}) / X_n \tag{2.4}$$

2.4 Predictive trend modelling

The output vector of the *dual net* are chosen to reveal the trend of price movement during the following six trading days.

2.4.1 Forward stochastic value: The traditional %K[k] value of the Stochastic Process reveals where the closing price of the current trading day stands relative to the retrospective fluctuation range of price in the last k trading days. The forward K[k] value represents where the closing price of the current trading day will stand in relation to the fluctuation range of price for the following k trading days. Any trader informed of this forward K[k] value can foresee the probability of a profitable trade during next k trading days from the position of buying stocks at the closing price of current trading day. We chose forward K[6] as the only element of the output vector. The best range of trading days chosen to look forward is still an open problem. There are two reasons for looking 6 days forward in our system. First, most short-term trends could only continue in the same direction for only 3 days. The profit gains for reversals shorter than 2 days are not significant enough for the traders to rush in and out the market. Secondly, fund managers and the dealing department of security companies can only sell (or buy) specific kinds of stocks until 2 trading days after the day they bold (or put) it. So, they are forced to predict the trend for the impending two or more trading days. The formula of forward K[6] is listed below.

$$\mathrm{ForwardK}_n[6] = \frac{C_n - \mathrm{MIN}_{i=n}^{n+6}(L_i)}{\mathrm{MAX}_{i=n}^{n+6}(H_i) - \mathrm{MIN}_{i=n}^{n+6}(L_i)} \tag{2-5}$$

3 System architecture

3.1 *Dual net* architecture

3.1.1 Primitive neural network modules: The network used in the present system is a *dual net* with two sets of multilayer feedforward neural networks which have been proved to be universal approximators of vector-valued functions [6]. Both sets of multilayer feedforward neural networks are composed of three identical primitive networks. Each primitive network consists of three layers: the input layer, one hidden layer, and the output layer. The input layer is made up of sixteen units each related to a projection value of the technical view of a selected stock on one of the sixteen axes spanning R_N. The output layer for each primitive network contains only one neuron which predicts the only element in the output vector. Each neuron in the primitive network calculates a weighted sum of its input and generates output using a standard sigmoid function. The architecture of the primitive network is illustrated in figure 1.

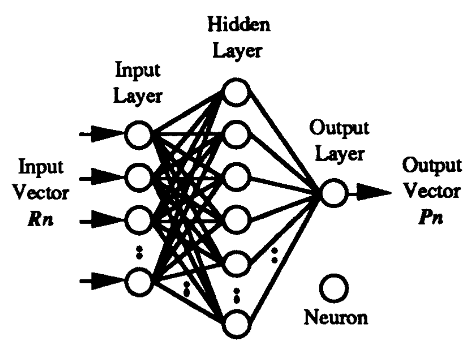

Figure 1

Primitive Neural Net Module of the *Dual Net*

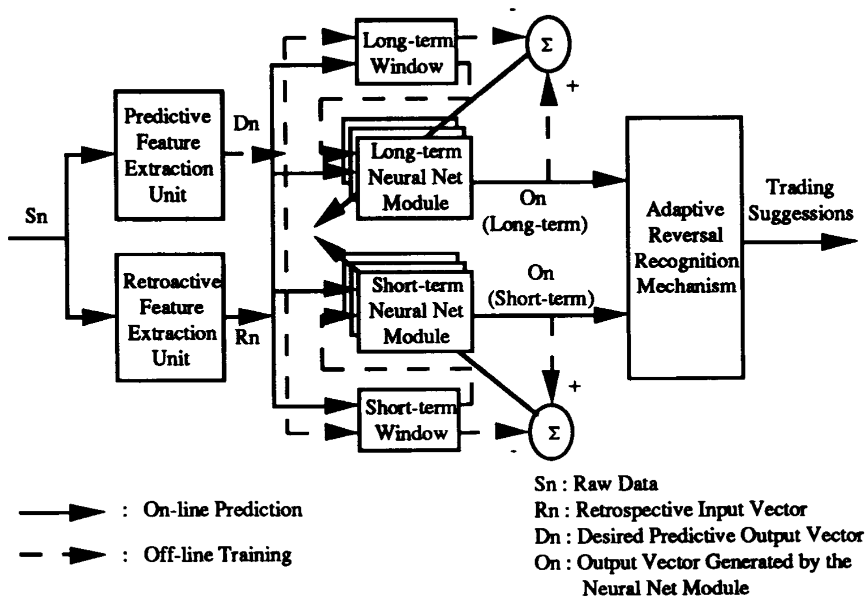

Figure 2
System Architecture

3.1.2 Why *dual net*: The short-term and long-term views for the technical characteristics of the Taiwan stock market are both established efficiently by feeding training patterns into each internal network of the *dual net* according to different selection schemes. While the short-term one utilizes a 12-day moving window, allowing only training patterns of the latest twelve days to pass, the long-term scheme filters data of the latest trading quarter in. The system architecture of the *dual net* is shown in figure 2.

The final output of the *dual net* is the weighted sum of the outputs generated by both neural network modules. Equipped with two view-points based on different levels of temporary dependence, the *dual net*, fails neither in tracking continuing trends, nor in quick response to major reversal of trends. We developed an adaptive weight adjusting algorithm which can tune the weights according to the prediction accuracy of each neural network module. Empirical analyses on the goodness of fit for nine approaches to generate the final prediction results have been done. In figure 3, type I and II method can predict the trends using the output of short-term and long-term neural network module respectively. Type III uses simple mean of both neural network modules. While type IV utilizes simple weighted sum of daily errors for the last six trading days, type V uses the linear weighted sum, and type VI uses the exponential weighted sum of daily error to adjust the weights. For type IV to VI, the changes made on the weights to compute the weighted sum of both neural network modules are adjusted according to the reciprocal of weekly errors made on the trend prediction. Type VII to IX are similar to type IV to VI, respectively, except that their weights are adjusted according to the reciprocal of the squared weekly errors.

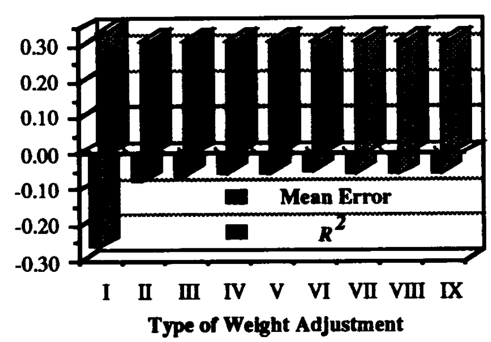

Figure 3 Comparison between nine ways to generate the prediction of short-term trends according to the raw result of the *dual net*

From figure 3, it is clear that the type V method, the linear weighted mean method, outperforms other methods for its features of better fitting ability and less average error on prediction. Also in figure 3, it is obvious that all the methods generating the prediction results using weighted sum of both neural network modules surpass those using single neural network modules. This proves the feasibility of our *dual net* architecture.

3.2 Modelling criterion

The quantitative measure of the goodness of the fit in the learning phase is given by the square of the sample correlation coefficient R.

$$R^2 = \frac{\sum_{i=1}^{n} (y_i - \overline{Y})^2 - \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{Y})^2} \tag{3.1}$$

Thus, R^2 measures the goodness of the fit between the *dual net* model and actual short-term trends of the stock market in the sense that it gives the proportionate reduction in the sum of squares of deviations obtained using the *dual net* relative to the naive predictor $\overline{Y}$.

3.3 Learning algorithm for the *dual net*

3.3.1 Two-mode back-propagation: A fast back-propagation learning algorithm [7] with two gears, one being normal and the other being faster due to using the selective updates of weights, is utilized in the *dual net*. Back-propagation with selective updates has been proposed in several papers [8]. Under such algorithm, the weights of each primitive network are changed only when the deviation between the generated output and the desired training pattern is larger than a specific threshold value. While keeping the learning process faster than conventional back-propagations at the initial training phase, the learning algorithm using selective updates of weights may suffer from the frequent oscillation near the local optimal and the induced low converging speed at the final training phase when the network is guided to generate extremely precise output for the training patterns containing some exceptions. To keep the learning speed fast throughout the whole learning process, the algorithm with selective weight updates is utilized at the initial and the major training phases for R^2 ranging from 0.0 to 0.9. And the normal back-propagation algorithm is used only in the final phase to fine-tune the weights [1].

3.4 Training scheme

3.4.1 Initial training: At the start-up time, the weights of each primitive network are all initialized with randomly generated numbers ranging from 0 to 701. Then the *dual net* is trained repeatedly with 288-day training patterns observed during one year before the prediction target date until the correlation coefficient R^2 is greater than 0.5. This initial training process guarantees that the global view of the characteristics of the short-term fluctuations observed over the latest trading year have been successfully fed into the *dual net*.

3.4.2 Moving-window training: A fixed stock market model may fail when the market behavior changes. To establish the temporary dependence in our stock market model, the moving-window training scheme is used to tune the weights of the *dual net* according to training data filtered by two fixed-width windows. So the *dual net* keeps track on both of the short-term and the long-term views for the characteristics of the short-term trends of the Taiwan stock market. The short-term module uses a 12-day moving window to adopt only the training patterns of latest twelve trading days into the training iteration. This 12-day moving window can keep the short-term module sensitive to the latest changes in the market behavior. The long-term module, on the other hand, concentrates on the data collected from the latest trading quarter. Equipped with two view-points based on different levels of temporary dependence, the *dual net*, fails neither in tracking continuing trends, nor in quick response to major reversal of trends.

4 Effective reversal pattern (ERP)

According to results of the empirical analyses on the Taiwan Stock Exchange Weighted Stock Index (TSEWSI), seventy percent of the raw reversals last less than two days. While recognizing all of the reversals is the optimistic goal for the *dual net*, recognition of more effective reversal patterns rather than small ripples of the major trend is more realistic. Thus different selection schemes are examined to identify the effective reversal patterns suitable for recognition using the trend prediction generated by the *dual net*. The moving average method is widely used to smooth out the erratic changes in actual prices and thereby indicates the underlying trend. But all the signals generated by the moving average method would be late by definition. These time lags are fatal when this method is applied to the recognition of short-term reversals. Although reducing the length of time used in computing the moving average can decrease the time lags, it also weakens the immunity for noisy data.

To keep both of the ability to indicate reversals precisely and the capability to suppress small ripples significantly in one selection scheme, a new method for the identification of the effective reversals is proposed. In this new selection scheme, the raw reversal patters are extracted first, and the length of each raw reversal is calculated. All the raw reversals with reversal ranges less than or equal to k days will be checked in the k-day rejection selection scheme. A short-term reversal will be preserved only when it is the local minima (or maxima) compared with the nearest neighboring reversals of the same style. The comparison between the nearest neighbors eliminates the ripples while keeping the major trends unchanged. In order to eliminate the distortions exerted by the convergent triangle-shape patterns, an extra look ahead window is included to eliminate all the ripples within the triangle. The example showing the results of 1-day rejection and 2-day rejection selection schemes is presented in figure 4.

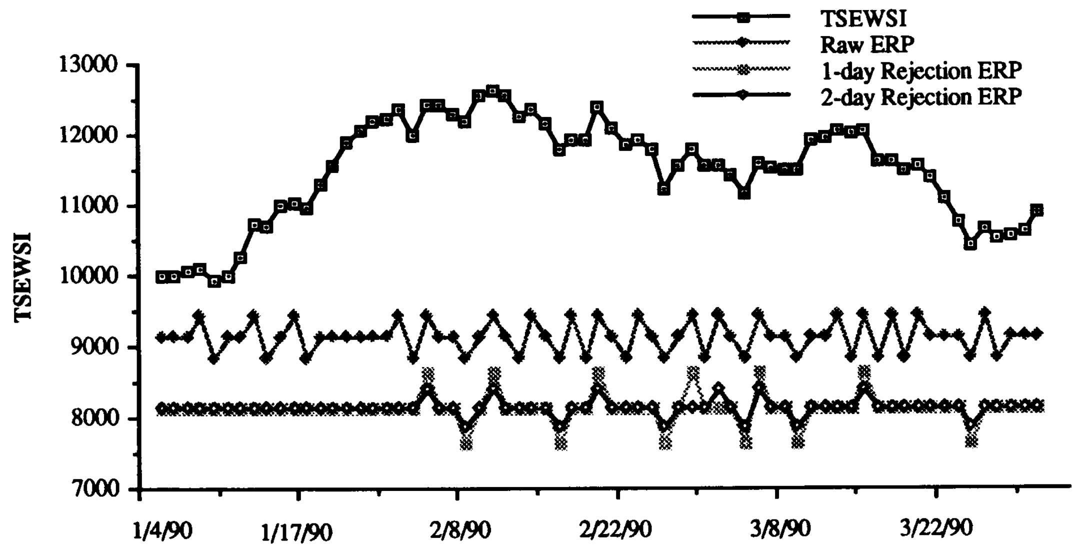

Figure 4
Examples of ERPs identified by different selection schemes

selection scheme	raw ERP		1-day rejection ERP		2-day rejection ERP	
reversal style	head	bottom	head	bottom	head	bottom
no. of occurrence	165	165	59	59	47	47
maximum of reversal length	7	12	21	26	24	26
average of reversal length	1.97	2.33	5.29	6.73	6.68	8.4
maximum of reversal range	-24.5%	+28.1%	-32.7%	+44.5%	-42.4%	+58.8%
average of reversal range	-4.7%	+5.3%	-9.9%	+12.3%	-11.4%	+14.5%

Table 1
Comparison between three ERP selection schemes applied to the TSEWSI for 707 trading days from January 1989 to June 1991.

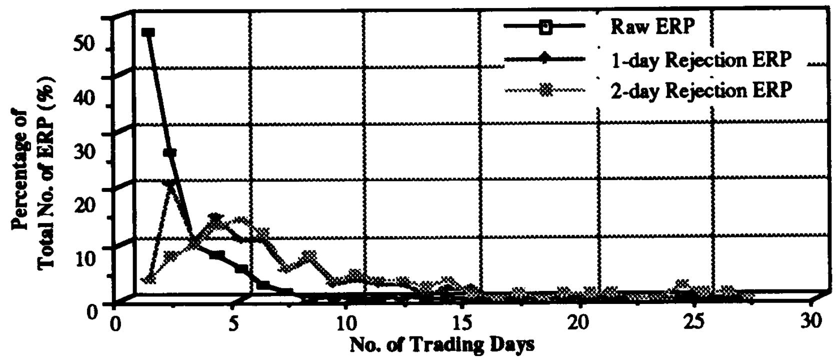

Figure 5 Comparison of the Reversal Length of Three Different ERPs

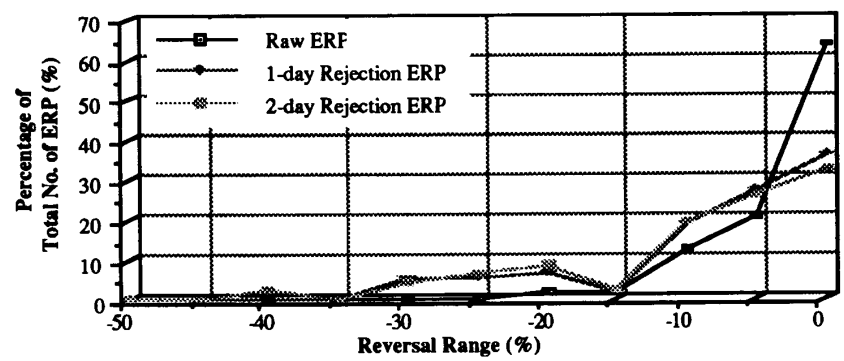

Figure 6.a Comparison of the Reversal Ranges for Head-style ERP

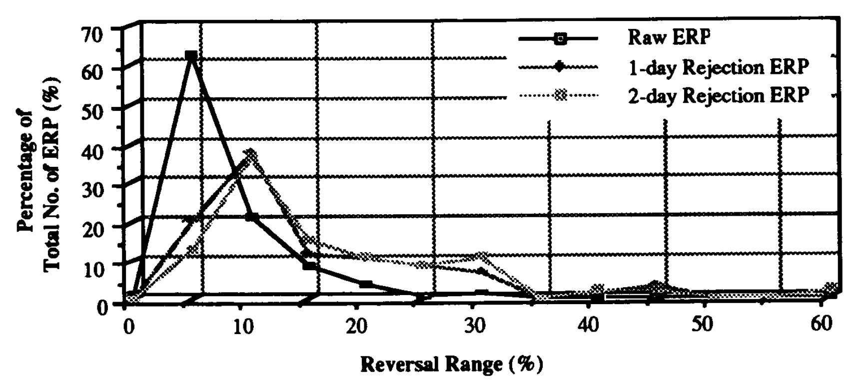

Figure 6.b Comparison of the Reversal Ranges for Bottom-style ERP

According to figure 5, table 1, figure 6.a and figure 6.b, the number of short-term reversals are reduced when k increases for the k-day rejection selection scheme, and the number of the reversals with small ranges is also decreased dramatically. Based on the analysis of the extracted ERP using different selection schemes listed in table 1, the 2-day rejection scheme is chosen to be the ERP selection scheme for the *dual net*.

5 ERP recognition

5.1 Comparison between the *dual net* and the multiple regression analysis

Table 2 shows the comparison of the goodness of fit (R^2) between the *dual net* and the multiple linear regression analysis.

	Long-term Window (72 trading days)		Short-term Window (12 trading days)	
	Dual Net	Multiple Linear Regression	*Dual Net*	Multiple Linear Regression
Mean of R^2	0.99	0.42	0.99	0.99
Std. Error of R^2	0.01	0.13	0.01	0.01

Table 2

Comparison of the goodness of fit (R^2)

The mean and standard deviation for both method are calculated from 10 set of the quarterly TSEWSI data collected from Spring 1988 to Summer 1990.

It is obvious that the *dual net* outperforms the multiple linear regression analysis for the fitting process over the long-term window. Although the *dual net* possesses better capability for modelling on the fluctuations over long-term trends, it performs just as well as the conventional regression analysis for modelling on short-term fluctuations.

5.2 Adaptive ERP recognition

The correlations between the predictive output vector of the *dual net* and the timing of the impending effective reversal trends have been examined. The values of the predictive output for each of the three consecutive trading days including 2 days before, 1 day before and the exact day starting the effective reversal trends are carefully studied by statistical analyses. The number of occurrences at different levels of the predictive output indices for the ERPs extracted by a specific selection scheme is used to illustrate the tendency of the market's behaviors.

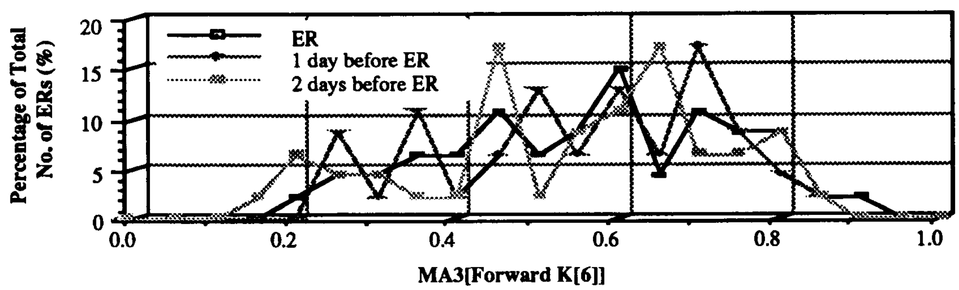

Figure 7.a The Relative Frequency of MA3[Forward K[6]] Values at the day of, 1 day before, and 2 days before the Head-style effective reversals

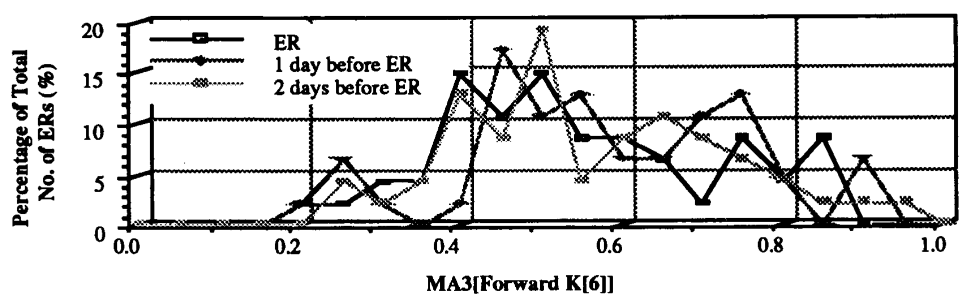

Figure 7.b The Relative Frequency of the MA3[Forward K[6]] Values at the day of, 1 day before, and 2 days before the Bottom-style effective reversals

From results shown in figure 7, the deviations of the frequency of the predictive indices of specific values are significant enough to isolate the impending head-style ERPs from bottom-style ones. Therefore the statistical characteristics of this dissimilarity can be used as important clues to identify the impending ERPs. The adaptive reversal recognition mechanism shown in figure 2 are designed under this discipline. When an ERP is met, the predictive outputs of the *dual net* are appended into a window of fixed width. Then the mean values and the standard deviations of these predictive indices within the window are calculated. Thus the thresholds used to decide whether or not there is an impending ERP are adapted according to the statistical characteristics calculated in real time.

6 Performance evaluation

The performance of the intelligent trend prediction and reversal recognition system based on the *dual net* is examined by simulating the buying and selling for the TSEWSI of the Taiwan stock market on the Sun SPARC Station 1 computer. Based on the statistical relationship between the predictive output of the *dual net* and the timing of impending short-term trends, the adaptive reversal recognition system which can self-tune its threshold is used to indicate the buying or selling signals according to the weighted sum of paired output from the *dual net*. The quarterly performances of buying and selling the TSEWSI using three kinds of investment strategies are examined. The first one of these strategies uses the raw predictive output of the *dual net*, and others utilize the 2-day and 3-day moving averages of that raw data. The algorithm for generating buying and selling signals using the raw data of the trend prediction generated by the *dual net* is listed below.

```
if (forward K_{n-1}[6] < lower threshold of BUY and
   forward K_n[6] > upper threshold of BUY)
then {
        if (BUY exists)
        then
                HOLD;
        else
                BUY;
}
if (forward K_{n-1}[6] > upper threshold of SELL and
   forward K_n[6] < lower threshold of SELL)
then {
        if (BUY exists)
        then
                SELL;
}
otherwise {
        HOLD;
}
```

Since the moving average can exponentially smooth out the variations, the false alarms caused by erroneous fluctuations are reduced. According to table 3, decisions made according to the moving averages generate larger return than that using the raw data.

7 Summary

A dual-module neural network (*dual net*) which can predict the short-term trends of price movement and recognize the effective reversals, is utilized to develop a more innovative, intelligent and profitable trend prediction and reversal recognition system for the Taiwan stock market. Novel transformations used to identify both retrospective and predictive features from raw data gathered from the market have also been presented.

Table 3 Performance Evaluation

Quarter	Initial TSEWSI	Final TSEWSI	Gain of TSEWSI	Buy&Sell Using Forward K[6]	Buy&Sell Using MA_2[Forward K[6]]	Buy&Sell Using MA_3[Forward K[6]]
1st Quar. 1989	4873.18	7390.15	+ 52 %	+ 7 %	+ 9 %	+ 8 %
2nd Quar. 1989	7275.74	9205.06	+ 30 %	+ 2 %	+ 28 %	+ 26 %
3rd Quar. 1989	8853.61	10180.84	+ 15 %	- 10 %	+ 4 %	+ 2 %
4th Quar. 1989	9911.15	9624.18	- 3 %	- 6 %	+ 14 %	+ 12 %
1st Quar. 1990	9853.15	10755.87	+ 9 %	- 6 %	- 6 %	+ 6 %
2nd Quar. 1990	11163.49	5049.58	- 55 %	- 49 %	- 38 %	- 47 %
3rd Quar. 1990	4905.87	2705.01	- 45 %	- 29 %	- 27 %	- 24 %
4th Quar. 1990	2560.47	4530.16	+ 77 %	+ 6 %	+ 16 %	+ 35 %
1st Quar. 1991	4258.93	5139.94	+ 21 %	+ 5 %	+ 15 %	+ 39 %
2nd Quar. 1991	5297.92	5613.10	+ 6 %	+ 0 %	+ 6 %	+ 1 %

Reinforcing the temporary correlations between the neural weights and the training patterns, the *dual net* with pairs of primitive networks are fine-tuned according to the patterns collected from windows of different sizes. The training time has been shortened using the two-mode back-propagation algorithm. According to the statistical features of the effective reversal patterns extracted by the ERP selection scheme, the thresholds for the 2-day rejection ERP recognizer can be adjusted to increase the hit ratio. Finally, due to the feature of acceptable returns shown in the performance evaluation, an intelligent trend prediction and reversal recognition system based on short-term trend prediction can be realized using the dual-module neural networks.

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