The KD-Based Neuro Fuzzy Trading Strategy

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Abstract

In this paper, a new trading decision strategy is proposed. This strategy combines the following concepts: KD-based rules, fuzzy logic inference mechanism and neural network learning ability. We used 115 stocks from different industries in Taiwan and their trading data during the period of Jan. 4, 1989 to June 30, 2000 as our experimental data. The data from Jan. 4, 1989 to Dec. 31, 1998 were used to train our decision rules and the data from Jan. 4, 1999 to June 30, 2000 were used to test the validity of our strategy, as compared with the buy and hold strategy and the KD trading system. The experimental results indicate that our strategy is significantly better than the other two strategies.

Keywords: neural network, fuzzy logic, buy and hold
1. Introduction

In general the approaches to predict stock price could be roughly categorized into two kinds, fundamental analysis and technical analysis. Fundamental analysis assumes that stock price is the function of fundamental variables, such as exports and imports, money supply, interest rates, foreign exchange rates, inflationary rates, unemployment figures, and the basic financial status of companies (Basu, 1977; Fama and French, 1992; Lakonishok, Shleifer and Vishny, 1994, Fernandez-Rodriguez, Gonzalez-Martel, and Sosvilla-Rivero, 2000). Technical analysis assumes that history will repeat itself and that the correlation between price and volume reveals market behavior. Prediction is made by exploiting the implications hidden in past trading activities and by analyzing the patterns and trends shown in the price and volume charts (Epps, 1975; Smirlock and Starks, 1985; Rogalski, 1978; Bohan, 1981; and Brush, 1986).

For technical analysis, some researches are exploring the statistically significant relationships between stock price and previous prices and/or quantities. Epps (1975) and Smirlock and Starks(1985) suggest that there is a positive correlation between the absolute value of price changes in the market and changes in transaction volume. Rogalski (1978) states that the knowledge of both prices and transaction volume information may be more valuable in predicting future stock movements than prices alone. Gencay (1998) construct the relationship between the rate of return and
signals calculated from the short term moving average and long term average.

On the other hand, since Lane (1957) and Wilder (1978) proposed the KD technical indexes and the relative strength indicator to do the trading respectively, some researches are curious in testing the efficiency of the filter rules. Bohan (1981) and Brush (1986) scientifically examine the usefulness of relative strength indicators and document a considerable degree of price persistence. Pruitt and White (1988) construct a trading system based on moving average, relative strength, and cumulative volume. Bessembinder and Chan (1995) use three simple filter rules, variable length moving average rules, fixed length moving average rules, and trading range break rules, to see whether they can be used to predict stock price movement in Asian markets. Parisi and Vasques (2000) also tests moving average and trading range break-out rules in the Chilean stock market.

Based upon Jacobs and Levy (1989), we somehow believe that it is necessary to use more complex rules for our trading strategies. Fuzzy logic allows us to describe sophisticated decision rules. For instance, in fuzzy logic, we may use terms such as very high and very low and so on. On the other hand, neural network is a good training method to finalize our decision rules based upon existing data. In this paper, we thus proposed a strategy which combines the KD rules, fuzzy logic and neural network.
2. The KD-Based Neuro Fuzzy Strategy

2.1 KD Trading System

The commonly used K D indicators are calculated as follows.

\[ RSV_t = \frac{(C_t - L_9)}{(H_9 - L_9)} \times 100 \]  
\[ K_t = \frac{1}{3} RSV_t + \frac{2}{3} K_{t-1} \]  
\[ D_t = \frac{1}{3} K_t + \frac{2}{3} D_{t-1} \]

where \( RSV_t \) is the raw stochastic value for period t, \( C_t \) is the closing price for day t, 
\( H_9 \) and \( L_9 \) are the highest price and the lowest price for the latest nine days respectively, \( K_t \) and \( D_t \) are the values for K and D on day t. If K and D are not available, 50 are used as the initial values for both in general. The trading rules for the KD trading system are as follows.

Rule 1. If D is greater than 80 then sell out. If D is less than 20 then buy in.

Rule 2. When K breaks through D from up, then sell out. When K breaks through D from down then buy in.

Whenever either rule is satisfied, the trading is conducted accordingly. Essentially KD indexes with the advantages of momentum, relative strength, and moving average, are expected to be capable of capturing the short-term variance. The above rules are in the spirit of the so called expert system because they are based on experience of experts. We must say that they are too simple. We will introduce the fuzzy logic
system in the next section.

2.2 Fuzzy Logic System

To capture the spirit of the traditional KD trading system, we need to choose the appropriate variables to describe the behavior of the above two rules. For rule 1, variables K and D would be enough to capture the relationship in rule 1. For rule 2, we need some variables to describe the cross over phenomenon. The cross over phenomenon when K breaks through D from up is depicted in Figure 2. Let K_D represent the difference between K and D, and K_D_1 represent the K_D of the previous day. If the cross over phenomenon happened, as depicted in Figure 2, then K_D_1 would be greater than 0 and K_D would be less than 0. Similarly, when K breaks through D from down, then K_D_1 would be less than 0 and K_D would be greater than 0. Therefore, we use K_D_1 and K_D to describe rule 2.

![Figure 2. The cross over phenomenon](image)

A fundamental idea of the fuzzy system is that we no longer say, for instance
that “IF K is greater than 80.” Instead, we will describe the value of K, for instance, to be very_low, low, medium_low, medium, medium_high, high, very_high. In other words, all the input and output variables will be translated into linguistic terms. Table 1 summarizes the KD related variables and their linguistic terms. Trend is calculated as \( (P_t - P_{t-1})/P_{t-1} \), where \( P_t \) represents the closing price on day \( t \). K, D, and Trend are all described by 7 terms. K_D, and K_D_1 are described by 2 terms. Each term is described by a membership function. A membership function, expressed as \( u_A(x) \), describes the extent an object \( x \) belongs to a fuzzy set (term) \( A \).

There are many different kinds of membership functions. Popular ones are Z, S, \( \lambda \) and \( \pi \) (Von Altrock et al 1992). In our case, we used Z, S, and \( \lambda \) for our experiments. Fig. 1(a), 1(b), 1(c), 1(d), 1(e) shows the membership functions for K, D, K_D, K_D_1, and Trend.
Figure 1(a). Membership function of “K”

Figure 1(b). Membership function of “D”
Figure 1(c). Membership function of “K_D”

Figure 1(d). Membership function of “K_D_1”
Consider the case where the value of K is 80, D is 60, K_D is 0.6 and K_D_1 is –0.4. It can be found in Figure 1(a) that the degree of K being high is 0.6 and the degree of K being very_high is 0.4. Besides, the degrees of K for other linguistics terms are all 0. The membership function for K equal to 80 can be expressed as K = \{very_low=0.0, low=0.0, medium_low=0.0, medium=0.0, medium_high, high=0.6, very_high=0.4\}. Similar to K, the values of the linguistic terms for the other variables can be found from Fig. 1(b), 1(c), and 1(d) as follows. D = \{very_low=0.0, low=0.0, medium_low=0.0, medium=0.2, medium_high=0.8, high=0.0, very_high=0.0\}. K_D = \{negative=0, positive=1\}, and K_D_1 = \{negative=1, positive=0\}.

After the numeric values have been translated into linguistic values, a much more sophisticated rule, for example, can be obtained as follows:

IF K is high, D is medium, K_D is positive and K_D_1 is negative, then Trend is high_inc.                                 \hspace{5em} (1)

This is so called an inference rule. Each rule consists of two parts, “IF” part and “THEN” part, describing the extent the real object satisfies the condition and the
response of this system respectively. The operator proposed by Zimmermann (1978) to represent logical connectives “and” is the minimum value among all the validity values. The validity of each term for rule (1) is summarized in table 2. Therefore, the validity value of the IF part is equal to \( \min\{0.6, 0.2, 1.0, 1.0\} = 0.2 \), which also indicates the degree of validity for the “THEN” part. In other words, the validity extent of the system’s response “TREND is high_inc” is 0.2.

Table 2. The corresponding validity extent of each term for rule (1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Values</th>
<th>Membership function</th>
<th>Validity</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>80</td>
<td>K is high</td>
<td>0.6</td>
</tr>
<tr>
<td>D</td>
<td>60</td>
<td>D is medium</td>
<td>0.2</td>
</tr>
<tr>
<td>K_D</td>
<td>0.6</td>
<td>K_D is positive</td>
<td>1.0</td>
</tr>
<tr>
<td>K_D_1</td>
<td>-0.4</td>
<td>K_D_1 is negative</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Note that using the rule “IF K is high, D is medium, K_D is positive and K_D_1 is negative, then Trend is high_inc.”, we will obtain the validity extent of “TREND is high-inc” is 0.2. However, there are 7 terms for K and D, 2 terms for K-D and K-D-1 and 5 terms for Trend. We have 7*7*2*2*5=980 rules to start with. Therefore, we have two problems: (1)How can we eliminate some of the inference rules which are not practical? (2)How can we use the remaining inference rules to obtain a precise value of TREND?

In the following, we shall discuss the second problem. The first problem, namely how to eliminate impractical rules, will be discussed later. Let us assume that we have, say five, inference rules. Using these five inference rules, we obtain the following inferences:
(1) The validity extent of “TREND is high_dec” is 0.0.
(2) The validity extent of “TREND is small_dec” is 0.3
(3) The validity extent of “TREND is steady” is 0.0
(4) The validity extent of “TREND is small_inc” is 0.2
(5) The validity extent of “TREND is small_inc” is 0.3

Note that there are the following five fuzzy set membership functions:
high_dec, small_dec, steady, small_inc, and high_inc. To facilitate discussion, let us
denote high-dec, small-dec, steady, small_inc, and high Inc by $f_1, f_2, f_3, f_4,$ and $f_5$
respectively. For each membership function $f_i$, let $M_i$ denote the value of TREND
which achieves the maximum value of $f_i$, if there are many values, the medium is
chosen. For instance, by consulting Fig. 1(e), we have the following mapping.

\[
\begin{align*}
M_1 &= -0.75 \\
M_2 &= -0.33 \\
M_3 &= 0.0 \\
M_4 &= 0.33 \\
M_5 &= 0.75
\end{align*}
\]

Let the validity extent of “TREND belongs to $f_i$” be denoted as $U_i$. Then
the value of TREND will be determined by the following formula:

\[
TREND = \sum_{i=1}^{5} U_i M_i
\]

Let us assume that $U_i$’s be 0.0, 0.3, 0.0, 0.2, and 0.3. We will have TREND
$= 0.0 \times (-0.75) + 0.3 \times (-0.33) + 0.0 \times 0 + 0.2 \times 0.33 + 0.3 \times 0.75 = 0.365$. This
means that predicted trend is 0.365 for the next day.

Buying signals are recognized when the predicted trend is greater than a
predetermined threshold value, and selling signals are recognized when it is less than
another predetermined threshold value. Usually both threshold values are set equal
to 0. Stocks are bought in when signal is greater than 0, and the stocks are held until the trend is less than 0. Buying signal is ignored when there are stocks on hold, and selling signal is ignored when there are no stocks on hold. In this paper, short sell strategy is not considered.

On the other hand, among all of these 980 rules, some of them are not valid in practical sense. For instance, the following rule obviously makes no sense:

IF D is very_low, K is very_low, K_D is negative and K_D_1 is negative, then Trend is high_inc.                                      (2)

Such a rule must be eliminated. Besides, how can we determine the membership function in this paper? The training method of neural network is used to refine the membership functions and eliminate irrelevant inference rules.

2.3 Neuro-fuzzy System

Let us first discuss how we can determine the membership functions as depicted in Fig. 1. Note that there are two parameters: (1) The shape of the membership functions. For instance, we may use Z, S, \( \hat{\lambda} \) and \( \pi \) shapes(Von Altrock et al 1992). We will not get into the details of how we choose the appropriate shapes. Let us assume that we have chosen one particular shape, say the shapes as described in Fig. 1.

Given a particular shape, we still can have different kinds of membership functions. For instance, for the K value, we may have the membership function in Fig. 3 to start with.
This membership function of $K$ is quite different from that in Fig. 1(a).

Similarly, we can have membership functions for $D$, $K_D$, $K_D_1$, and TREND which are different from those in Fig. 1. The training procedure feeds data from 1992 to 1999 into our system containing many inference rules and obtains values of predicted TREND’s. For each predicted TREND, we compare it with the actual value and we have a mechanism to adjust the membership functions in such a way to minimize the difference.

Let us now introduce how we eliminate irrelevant inference rules. Note that in the above discussion, we assumed that each rule is of each weight. In reality, we shall give each inference rule a weight. Initially, all inference rules are of equal weights. Using all of the inference rules, we can obtain a value of predicted TREND for a given set of training data. Again, we compare this predicted TREND value with the actual value. There will of course be a certain amount of difference. We now adjust the weight. Let us consider, say Rule $i$. We either increase the weight
of this rule or decrease it. For each case, we find out whether it improves our prediction. We always increase, or decrease, the weight to decrease the difference between the predicted TREND and the actual TREND. This is our training process. We continue to adjust the weights of all of the 980 inference rules until the difference between the predicted and the actual TREND is small enough. During the training process, if the weight of an inference rule is smaller than a certain value, it is discarded. This training process is in the spirit of the idea proposed by (Kosko 1992).

At the end of our training process, 245 rules remain to be used. We give 20 of them in Table 2.

Table 2. Part of the knowledge base after training for one randomly chosen series

<table>
<thead>
<tr>
<th>IF</th>
<th>THEN</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>K</td>
</tr>
<tr>
<td>Very_low</td>
<td>very_low</td>
</tr>
<tr>
<td>Very_low</td>
<td>very_low</td>
</tr>
<tr>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>medium_high</td>
<td>medium_high</td>
</tr>
<tr>
<td>medium_high</td>
<td>medium_high</td>
</tr>
<tr>
<td>medium_high</td>
<td>medium_high</td>
</tr>
<tr>
<td>medium_high</td>
<td>High</td>
</tr>
<tr>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Very_low</td>
<td>very_low</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>High</td>
<td>medium_high</td>
</tr>
<tr>
<td>Low</td>
<td>very_low</td>
</tr>
<tr>
<td>High</td>
<td>high</td>
</tr>
<tr>
<td>Medium</td>
<td>medium</td>
</tr>
<tr>
<td>very_high</td>
<td>very_high</td>
</tr>
<tr>
<td>medium_high</td>
<td>medium</td>
</tr>
<tr>
<td>medium_low</td>
<td>medium_low</td>
</tr>
<tr>
<td>medium_high</td>
<td>medium_low</td>
</tr>
<tr>
<td>very_high</td>
<td>High</td>
</tr>
<tr>
<td>medium_low</td>
<td>very_low</td>
</tr>
</tbody>
</table>

In the following, we give a summary of our strategy:

1. Our KD-based decision rules involve four input variables, namely K, D, K-D
2. We use the fuzzy logic concept to describe each variable. The numbers of linguistic terms that K, D, K-D, K-D-1 and Trend have are 7, 7, 2, 2 and 5 respectively. Thus the number of possible decision rules is

\[ 7 \times 7 \times 2 \times 2 \times 5 = 980. \]

3. A set of stocks will be randomly selected and their trading data will be collected. An early part of the data will be used as the training data.

4. For each stock, the neural network techniques are used to eliminate rules which are incompatible with our training data. For instance, consider the rule:

“If D is very low, K is very low, K-D is negative, K-D-1 is positive, then Trend is high-inc.” This is a typical rule, among the 980 ones, which the neural network technique will eliminate for any stock.

5. The training process is terminated when the predicted trend by using our decision rules is quite close to the real data. Thus, for each stock, there will be a set of rules associated with it and our KD-based neuro-fuzzy strategy uses the rules produced by this training process to forecast the next day trend of this stock.

3. Empirical Results

In this study, 115 stocks, 20% of all stocks in each industry in Taiwan's
Stock Market were randomly selected as the sample data. The data were collected in the period of January 4, 1989 to June 30, 2000, and divided into two parts, training data set and testing data set. Training data set is from Jan. 4, 1989 to Dec. 31, 1998. Testing data set is from Jan. 4 1999 to June 30, 2000. Training data is used to train the knowledge base among the technical indexes and stock price change. Testing data is used to test the validity of the constructed model. In this experiment, we implemented three strategies, namely the buy and hold strategy, the KD strategy and our KD based neuro fuzzy strategy. We used the following parameters to measure the quality of the strategies: rate of return, profit factor, direction forecasting, cumulative wealth, maximum drawdown and average drawdown, and Sharpe ratio.

3.1 Rate of Return

In our experiment, we used geometric average as the rate of return for each trading strategy. Let $R_i$ denote the rate of return of trade $i$ (buy and sell). It is calculated as follows,

$$R_i = [(P_{sell} - P_{buy}) \times (1 - Fee_{sell} - Tax_{sell}) / (P_{buy}) \times (1 + Fee_{buy})] - 1,$$

(4)

where $P_{buy}$ is the buying price, $P_{sell}$ is the selling price, $Fee_{sell}$ and $Fee_{buy}$ are the transaction costs when selling and buying the stock respectively and $Tax_{sell}$ is the tax when selling the stock. In Taiwan $Fee_{sell}$ and $Fee_{buy}$ are the same for 0.1425%, and $Tax_{sell}$ is for 0.3%. The yearly rate of return for the neuro-fuzzy, $R_{nf}$, is calculated as follows.
$R_{nf} = [(1 + R_1) \times (1 + R_2) \times \cdots \times (1 + R_t)]^{\frac{1}{n}} - 1$  \hspace{1cm} (5)

where $n$ is the measure of how many years for the simulation period. The yearly rate of return of buy and hold strategy, $R_{B\&H}$, is calculated as follows.

$R_{B\&H} = [(P_i - P_1) \times (1 - Fee_{sell} - Tax_{sell})/(P_1) \times (1 + Fee_{buy})]^\frac{1}{n} - 1,$  \hspace{1cm} (6)

where $P_i$ is the closing price for the first day of the simulation period, $P_f$ is the closing price for the last day of the simulation period. Table 3 shows the basic statistics for the yearly rate of return for each strategy. Table 4 shows the paired test among these three trading strategies. The values in Table 4 represent the difference between the rate of return of the strategy at the row and the rate of return of the strategy at the column. For example, the difference of rate of return between neuro fuzzy and buy and hold strategy is equal to 0.229, with statistical significance at $\alpha$ equal to 0.01.

Table 3. Basic statistics for the yearly rate of return

<table>
<thead>
<tr>
<th>Period</th>
<th>Strategy</th>
<th>Mean of rate of return</th>
<th>No. of stocks</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing</td>
<td>Buy and Hold</td>
<td>0.0188</td>
<td>115</td>
<td>0.408476</td>
</tr>
<tr>
<td></td>
<td>KD Index</td>
<td>-0.0200</td>
<td>115</td>
<td>0.262699</td>
</tr>
<tr>
<td></td>
<td>NeuroFuzzy</td>
<td>0.2470</td>
<td>115</td>
<td>0.351308</td>
</tr>
</tbody>
</table>

Table 4. Paired tests of the yearly rate of return

<table>
<thead>
<tr>
<th></th>
<th>Buy and Hold</th>
<th>KD indexes</th>
<th>Neuro Fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy and Hold</td>
<td>--</td>
<td>0.039 (0.210)</td>
<td>-0.229 (0.000)**</td>
</tr>
<tr>
<td>KD indexes</td>
<td>-0.039 (0.210)</td>
<td>--</td>
<td>-0.267 (0.000)**</td>
</tr>
<tr>
<td>Neuro Fuzzy</td>
<td>0.229 (0.000)**</td>
<td>0.267 (0.000)**</td>
<td>--</td>
</tr>
</tbody>
</table>

( ** : P-Value < 0.01)
Table 4 indicates that the rate of return of neuro-fuzzy is significantly
greater than that of both KD trading system and buy and hold strategy.

3.2 Profit Factor

The profit factor (Wolberg 2000) is defined as the ratio of the profit on winning trades
divided by the loss on losing trades. It is calculated as follows,

\[
profit\ factor = \frac{\text{profit on winning trades}}{\text{loss on losing trades}}
\]  

(7)

A value of profit factor less than one implies that the trading system will lose money
over the long run. A value greater than one implies a profitable trading system.

Table 5 shows the basic statistics of the profit factors for KD trading system
and neuro-fuzzy system. Table 6 shows the tests whether the profit factor is greater
than one or not for both methods.

Table 5. Basic statistics for Profit Factor

<table>
<thead>
<tr>
<th>Strategy</th>
<th>No. of stocks</th>
<th>Mean of profit factor</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>KD</td>
<td>94</td>
<td>1.8556</td>
<td>2.1651</td>
</tr>
<tr>
<td>Neuro Fuzzy</td>
<td>112</td>
<td>4.0675</td>
<td>11.0462</td>
</tr>
</tbody>
</table>
Table 6. Test for null hypothesis that profit factor equals to one

<table>
<thead>
<tr>
<th>Profit Factor</th>
<th>Test Value</th>
<th>df</th>
<th>t</th>
<th>Sig. (2-tailed)</th>
<th>95% Confidence Interval of the Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Lower</td>
</tr>
<tr>
<td>NeuroFuzzy</td>
<td>4.07</td>
<td>111</td>
<td>2.939</td>
<td>0.004**</td>
<td>0.999</td>
</tr>
<tr>
<td>KD Index</td>
<td>1.86</td>
<td>93</td>
<td>3.831</td>
<td>0.000**</td>
<td>0.412</td>
</tr>
</tbody>
</table>

( ** : P-Value < 0.01 )

It can be seen that the profit factors of both neuro fuzzy and KD systems are significantly greater than 1. In other words, both neuro fuzzy and KD system can be profitable in the long run.

3.3 Direction Forecasting

In addition to the rate of return, percentage of correct predictions of the direction are also computed for each trading strategy. Table 7 shows the basic statistics of correct prediction percentage for the 115 series by using our neuro fuzzy strategy. Table 8 indicates that the correct prediction percentage is significantly greater than 50% at 0.01 significance level. Note that the direction forecasting is not meaningful for both buy and hold and KD strategies.
### Table 7. Basic statistics for of correct prediction for the direction

<table>
<thead>
<tr>
<th>Strategy</th>
<th>No. of stocks</th>
<th>Mean of correct prediction percentage</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NeuroFuzzy</td>
<td>115</td>
<td>0.5395</td>
<td>0.03372</td>
</tr>
</tbody>
</table>

### Table 8. Test for null hypothesis that correct prediction percentage equals to 0.5

<table>
<thead>
<tr>
<th>Strategy</th>
<th>t</th>
<th>df</th>
<th>Sig. (2-tailed)</th>
<th>Mean Difference</th>
<th>95% Confidence Interval of the Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NeuroFuzzy</td>
<td>20.154</td>
<td>114</td>
<td>0.000**</td>
<td>0.085</td>
<td>0.077 - 0.094</td>
</tr>
</tbody>
</table>

( ** : P-Value < 0.01 )

### 3.4 Cumulative wealth

Table 9 shows the basic statistics of the cumulative wealth for 115 series.

Table 10 shows the paired test among these three trading systems. Figure 4 shows the cumulative wealth of these three trading strategies for one randomly chosen series, whose pattern is typical for most of the series.

### Table 9. Basic statistics for cumulative wealth

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean of cumulative wealth</th>
<th>No. of stocks</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NeuroFuzzy</td>
<td>1247.07</td>
<td>115</td>
<td>351.308</td>
</tr>
<tr>
<td>KD Index</td>
<td>979.99</td>
<td>115</td>
<td>262.699</td>
</tr>
<tr>
<td>Buy and Hold</td>
<td>1018.83</td>
<td>115</td>
<td>408.476</td>
</tr>
</tbody>
</table>
Table 10. Paired test of cumulative wealth

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>KD indexes</th>
<th>Neuro fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy and hold</td>
<td>--</td>
<td>38.841 (0.210)</td>
<td>-228.235 (0.000)**</td>
</tr>
<tr>
<td>KD indexes</td>
<td>-38.841 (0.210)</td>
<td>--</td>
<td>-267.076 (0.000)**</td>
</tr>
<tr>
<td>Neuro fuzzy</td>
<td>228.235 (0.000)**</td>
<td>267.076 (0.000)**</td>
<td>--</td>
</tr>
</tbody>
</table>

( □ = 0.05, ** : P-Value < 0.01 )

Table 10 shows that the cumulative wealth of neuro fuzzy is significantly greater than that of both traditional KD trading system and buy and hold strategy.

Figure 4. Cumulative wealth for one randomly chosen series for three different strategies during the testing period
3.5 Maximum Drawdown and Average Drawdown

The drawdown (Wolberg 2000) at any given moment is the fractional decrease in equity from the previous equity high point. It is defined as follows.

\[
drawdown = 1 - \frac{equity}{\text{max equity}},
\]

where max equity is the maximum value of the equity ever reached during the testing period. The maximum and average drawdown are the maximum value and average value of drawdown during the simulation period, respectively.

Table 11 shows the basic statistics of maximum draw-down and average draw-down for these three trading strategies. Table 12 shows the paired test among these three trading strategies.

Table 11. Basic statistics for max draw down and average draw down

<table>
<thead>
<tr>
<th>Items</th>
<th>Strategy</th>
<th>Mean</th>
<th>No. of stocks</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max Draw Down</td>
<td>NeuroFuzzy</td>
<td>0.292</td>
<td>115</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>KD Index</td>
<td>0.346</td>
<td>115</td>
<td>0.144</td>
</tr>
<tr>
<td></td>
<td>Buy and Hold</td>
<td>0.506</td>
<td>115</td>
<td>0.138</td>
</tr>
<tr>
<td>Average Draw Down</td>
<td>NeuroFuzzy</td>
<td>0.107</td>
<td>115</td>
<td>0.059</td>
</tr>
<tr>
<td></td>
<td>KD Index</td>
<td>0.159</td>
<td>115</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>Buy and Hold</td>
<td>0.268</td>
<td>115</td>
<td>0.117</td>
</tr>
</tbody>
</table>

It can be seen from table 12 that both the maximum draw-down and average draw-down of neuro-fuzzy are significantly less than those of both KD trading system and buy and hold strategy.
Table 12. Paired test for maximum draw down and average draw down

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>KD indexes</th>
<th>Neuro fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Max Draw Down</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buy and hold</td>
<td>--</td>
<td>0.160</td>
<td>0.214</td>
</tr>
<tr>
<td>KD indexes</td>
<td>-0.160 (0.000)**</td>
<td>--</td>
<td>0.053 (0.000)**</td>
</tr>
<tr>
<td>Neuro fuzzy</td>
<td>-0.214 (0.000)**</td>
<td>-0.053 (0.000)**</td>
<td>--</td>
</tr>
<tr>
<td><strong>Average Draw Down</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buy and hold</td>
<td>--</td>
<td>0.109 (0.000)**</td>
<td>0.161 (0.000)**</td>
</tr>
<tr>
<td>KD indexes</td>
<td>-0.109 (0.000)**</td>
<td>--</td>
<td>0.052 (0.000)**</td>
</tr>
<tr>
<td>Neuro fuzzy</td>
<td>-0.161 (0.000)**</td>
<td>-0.052 (0.000)**</td>
<td>--</td>
</tr>
</tbody>
</table>

( ** : P-Value < 0.01 )

3.6 Sharpe Ratio

Sharpe ratio (1966) is simply the mean return of the trading strategy divided by its standard deviation. It measures the risk premium earned per unit of risk exposure. It is calculated as follows.

\[
\text{Sharpe ratio} = \frac{\text{roi}}{\sigma}
\]

(9)

where \( \text{roi} \) is the average daily rate of return, and \( \sigma \) is the standard deviation of the rate of return. Higher Sharpe ratio implies higher rate of return given a fixed volatility or lower volatility given the fixed rate of return.

Table 13 shows the basic statistics of sharpe ratio for these three trading system. Table 14 shows the paired test among them.
Table 13. Basic statistics for Sharpe ratios

<table>
<thead>
<tr>
<th>Sharpe Ratio</th>
<th>Mean of Sharpe Ratio</th>
<th>No. of stocks</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing Period</td>
<td>Buy and Hold</td>
<td>0.0080</td>
<td>115</td>
</tr>
<tr>
<td></td>
<td>KD Index</td>
<td>0.0024</td>
<td>115</td>
</tr>
<tr>
<td></td>
<td>NeuroFuzzy</td>
<td>0.0394</td>
<td>115</td>
</tr>
</tbody>
</table>

Table 14. Paired test for Sharpe ratios

<table>
<thead>
<tr>
<th></th>
<th>Buy and hold</th>
<th>KD indexes</th>
<th>Neuro fuzzy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy and hold</td>
<td>--</td>
<td>0.0055</td>
<td>-0.0315** (0.000)**</td>
</tr>
<tr>
<td>KD indexes</td>
<td>-0.0055 (0.089)</td>
<td>--</td>
<td>-0.037 (0.000)**</td>
</tr>
<tr>
<td>Neuro fuzzy</td>
<td>0.0315 (0.000)**</td>
<td>0.037 (0.000)**</td>
<td>--</td>
</tr>
</tbody>
</table>

(* * : P-Value < 0.01)

It can be seen from table 14 that the sharpe ratio of neuro-fuzzy is significantly greater than that of traditional KD trading system and buy and hold strategy.

5. Conclusions

In this paper, we basically assume that the parameters, K, D and so on, are important and informative parameters which can be used to predict the stock prices. Yet, one must have rather complicated rules. Thus we use fuzzy terms to describe the parameters. We also propose to use fuzzy logic in our decision mechanism. Thus, we will use a set of fuzzy logic inference rules for our prediction. These rules are obtained by using the neural network training method and a set of real data. The final rules will be compatible with our real life data. Experimental results show that the rules obtained by this training process are significantly better than the buy and
hold method and the K-D rules as measured by rate of return, profit factor, direction forecasting, cumulative wealth, maximum drawdown and average drawdown, and Sharpe ratio.
References


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