The Quantitative Machinery Decision-Making Strategy Model Based on Neural Network

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Abstract. High-frequency data and quantitative models are the hot issues in the machinery field. In order to build a quantitative strategy with steady returns and relatively low risks based on high frequency data, this paper establishes a quantitative machinery selection strategy based on difference flow and a time-selection strategy based on neural network. Through our research on China's machinery market, we find that when using fund flow intensity as an indicator, the market yield of the portfolio with large capital flow is relatively high. After selecting some companies with potential upside, we used a neural network algorithm to predict the value between both sides. Using these technical indicators and historical information, we use neural networks to predict the next day's closing value. Finally, we simulated the decision with Matlab, and analyzed the profitability and risk factors of our strategy in different periods of the machinery market, and drew the final conclusion.

1. Introduction

In recent years, high-frequency data analysis is undoubtedly one of the frontier hot issues in the financial field. The innovation of information technology has made it easier for investors, environmental friendly decision-making model institutions and research institutions to obtain high-frequency trading data, thus effectively analyzing the nature of the market, avoiding financial risks, promoting the allocation of market resources and promoting the development of division of labor.

High-frequency data can show us some microstructure effects in the market, such as bid-ask spread and value, which bring many challenges to the modeling and analysis of high-frequency data. Ultimately, all forecasts and analysis should be trading services. How to use the high-frequency trading data to establish an appropriate mathematical model, and predict the future trend of machineries and the right environmental friendly decision-making model time according to the model, and then increase the profits of investors as much as possible, is the problem to be solved in this paper.

Quantitative environmental friendly decision-making model is an environmental friendly decision-making model method that USES knowledge tools such as finance, mathematics and computer to make decisions by building models. Due to its unique nature, relatively stable returns and ever-expanding market size, quantitative environmental friendly decision-making model has been favored by more and more investors due to its many advantages [1].
2. Neural network and environmental friendly decision-making model

In system theory, the description and recognition of unknown systems is of vital importance. The description of the system involves how the mathematical model is used to describe the system.

The theoretical principle of using neural network for approximation is as follows: "in the case that the activation function has a continuous bounded number of multi-layer neural networks (even if there is only one hidden layer), in the case that the hidden layer has sufficient number of nodes, any continuous function can be uniformly approximated on the compact set of the input space". Neural network is widely used in the fields of pattern recognition, pattern classification, image processing, signal processing and signal control because of its strong fitting ability to the nonlinear complex function mapping and fuzzy information [2].

![Figure 1. The principle of the neural network.](image)

The function relation of machinery is nonlinear and time series. Since non-efficient markets assume that changes in machinery values are not disorderly, we should be able to take a look at historical value changes. How to predict the change of machinery value from historical data becomes a problem for us. Because of the strong fitting ability of artificial neural network, the application of artificial neural network to predict the future value of machineries becomes our solution to this problem.

2.1. Non-efficient decision-making hypothesis

There have been two opposing views about whether share values can be predicted. Before the efficient market hypothesis was proposed, scholars generally studied directly whether the machinery value could be predicted, but after that, the focus of the research turned to the question of whether the market was effective. The reason for this shift is that the purpose of machinery value forecasting is to guide environmental friendly decision-making model to obtain excess returns Meaningless. That is to say, if the market is recognized to be effective, then any environmental friendly decision-making model method cannot obtain the excess returns, in other words, any machinery valuation method, forecast method research is meaningless [3].

In terms of the research on the effectiveness of China's machinery market, li guoping expounds the concept of machinery market prediction from a qualitative perspective, and theoretically illustrates that China's machinery market does not satisfy the weak effective hypothesis. Dong xuejian analyzed the efficiency of Shanghai machinery market by statistical method, and found that the use of technical analysis can help the prediction of future earnings, which indicates that Shanghai machinery market has not achieved the weak efficiency. Xie jing also conducted an effective market test on chinext, and found that although our chinext market has some characteristics of an effective market, it is still not weak and effective. All the papers show that the machinery market in China is still not a weak efficient market. Therefore, we can use certain methods to estimate and predict the machinery market. This is also the presupposition that our trading strategy can achieve results [4-6].
2.2. Selection of technical parameters

In order to use neural network to predict future machinery values, we must find the parameters of the appropriate technical indicators as independent variables. Let's say we want to predict $Y$ is the closing value for the next day, and then we have to think about what technical indicators can affect the closing value for the next day. Generally speaking, technical indicators are mainly divided into four categories: trend indicators, overbought and oversold indicators, popularity indicators and general trend indicators. These four categories of indicators also become the core indicators of our forecast machinery value. The specific meaning and calculation formula are as follows:

a) Indicators of trend category

   Moving Average, a technical index used by MA to Average machinery values over a period of time by means of statistical analysis. This parameter is the average closing value of the last five days and the average closing value of the last 20 days.

   MACD index is obtained by performing double smoothing on the slow (long term) and fast (short term) moving averages and their aggregation and separation signals. The index consists of DEA and DIF. In our case, we chose 26 for slow (long term) and 12 for fast (short term), because this option is commonly used. When calculating the DEA, the difference of 9 consecutive days was selected as the average. The specific calculation formula is as follows.

b) Overbought and oversold indicators

   The William indicator represents the relative position of the closing value of the day over the entire value range of the past period. If the value of William index is relatively large, it means that the value of the day is relatively high, so you should be wary of falling back. If the value of William index is relatively small, it means that the value of the day is relatively low, so you should pay attention to the rebound.

   KDJ indicators, according to the principle of statistics, seen through a special period of the cycle of the highest and the lowest value and the last calculation cycle and at the close of the proportion of the relationship between the three, to calculate a computational cycles of immature random value RSV, then according to the smooth moving average method to calculate the K value, D and J values, painted with graph machinery movements. In this case, the cycle we choose is one day. It is also to distinguish between the KDJ indicator and the William indicator [7].

3. Quantifying the construction of a timing strategy

Through the neural network, we can simulate the non-linear relationship between the machinery's closing value and the above 15 parameters (plus the closing value of the day). In this way, by training the neural network with the appropriate data set, we can get the proper function of predicting machinery closing value of the next day. And for a particular machinery, on that day, we can use this neural network to predict the machinery's closing value for the next day by entering information about the top 15 parameters of the machinery. If the next day's value is higher than our closing value for the day, we buy with our closing value for the day. And if the next day is lower than our closing value, if we hold this machinery, then we're all out of it; if we do not own the machinery, then we continue to wait and see until we judge the value is higher than the closing value of the day.

Through the fund flow quantitative machinery selection method, we can get the machinery with the smallest fund flow on a certain day. Such machineries have a lot of potential to go up over the next period of time. But the general method of quantitative machinery selection is fixed time sale, cannot achieve precision sale. On the other hand, through our neural network simulation, we can use each indicator to predict the next day's closing value. Such predictions are biased, but not by much. However, the neural network time-of-use trading model can only operate on a single machinery. Although it can be sure that it will be sold on a certain day, it has a great demand on the machinery market.

So combining the two approaches, complementing each other, becomes our trading strategy. We first select the five machineries companies with the most potential to rise through the fund flow quantitative machinery selection method, and then carry out quantitative timing operations on these five machineries respectively within a certain period of time. When the time period is over, we trade another five with
potential by quantitative machinery selection, and then do the same thing with quantitative timing, and so on. In this way, through the quantitative machinery selection method, we have selected the most promising, and through the quantitative timing method, we can effectively avoid the five companies that may fall, only the stage of its possible rise has been traded. The two methods complement each other and perfect our strategy.

4. Fund flow quantitative machinery selection strategy results

First, we divided the period from January 2, 2014 to June 30, 2017 into consolidation, bull market, bear market and slow bull market according to the yield of CSI 300 index.

For each 5-day environmental friendly decision-making model period, we use the fund flow strength machinery selection method to preliminarily select 5 pre-invested machineries, specifically 5 machineries with the maximum net fund flow at the observation period of 11 days. To further test our fund flow machinery selection strategy, we examined the daily machinery portfolio yield.

It can be seen from the result analysis that the top portfolio composed of the five machineries with the strongest capital flow intensity has a 67.7% probability of obtaining a positive return, higher than the market portfolio (equal weight portfolio) has a 63.7% probability of obtaining a positive return. At the same time, the top portfolio has a 72.4% chance of outperforming the market portfolio. They proved that our machinery selection strategy is effective.

| result | Environmental friendly decision-making model periods | Positive period | Earnings above the market average |
|--------|------------------------------------------------------|-----------------|-----------------------------------|
| top5   | 836                                                  | 566             | 604                               |
| bottom5| 836                                                  | 467             | 373                               |
| market | 836                                                  | 533             |                                   |

To sum up, our environmental friendly decision-making model strategy is active in the bull market, try to stop losses in the bear market, reduce risks in the consolidation period, conservative environmental friendly decision-making model. One of the advantages of our environmental friendly decision-making model strategy is that it responds differently to three different machinery market situations.
5. Conclusion

Based on the assumption that environmental friendly based machinery market is not a weak efficient market, we use some indicators to predict future machinery values. As the dynamic process of machinery value change is very complex, the relationship between some parameters and machinery value is not simply linear. Therefore, this paper USES neural network to predict machinery value.

In this paper, the technical indicators are mainly divided into four categories: trend indicators, overbought and oversold indicators, popularity indicators and general trend indicators. Through the neural network, we can simulate the non-linear relationship between the machinery's closing value and the above 15 parameters (plus the closing value of the day). In this way, by training the neural network with the appropriate data set, we can get the proper function of predicting machinery closing value of the next day. The decision to buy, sell, hold, or stay on the sidelines is made by comparing tomorrow's values to today's.

The advantages of this model is quantified by the cash flow to pick machinerys and machinery selection algorithm based on neural network is combined with the two methods complement each other, through the quantitative machinery selection method, we selected the most potential of machineries, and through the quantitative timing method, can effectively avoid the five companies could fall stage, only to be likely to rise stage to do the deal. The advantages of the two methods complement each other and make the strategy more perfect.

At the same time, we mainly divide the machinery market into bull market, bear market and consolidation period, and evaluate our quantitative environmental friendly decision-making model strategy based on different machinery market periods. Our environmental friendly decision-making model strategy is aggressive in the bull market, stops losses in the bear market, reduces risk in the consolidation period, and invests conservatively. One of the advantages of our environmental friendly decision-making model strategy is that it responds differently to three different machinery market situations.

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