2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)

Stock Reversal Pattern Mining Based on Fuzzy Candlestick Lines

Yongqiang Pei, Jiawei Wang, Xueqing Tang
College of Information Science and Engineering
Chongqing Jiaotong University
Chongqing, China
Email:p8192844@163.com

Abstract—**The stock financial time series contains information on the objective laws of the stock market, which reflects the psychological changes of investors to some extent. Candlestick lines theory is an empirical model of investment decision-making. The candlestick-line model reflects market psychology, and investors can make investment decisions based on the identified candlestick-line model. In view of the numerous and complicated parameters of the existing candlestick-line mining technology, it is difficult to be understood by the general investors. It is proposed to apply fuzzy logic to the traditional candlestick-line graph theory. Based on the definition of the stock price reversal trend, the fuzzy candlestick-line reversal feature is used to Reverse mode to classify. The empirical research on the two securities markets of SSE A shares and Shenzhen Stock Exchange A shares shows that the fuzzy logic candlestick-line reversal mode proposed in this paper exists and can be classified and identified.**

Keywords—Candlestick lines; Reversal Pattern; Investment income

I. INTRODUCTION

The stock market is receiving more and more attention in today's economic life. The trend of the stock market is affected by a variety of economic, political, and cultural factors. The operating rules are complex. It is important for traders to grasp the laws of the market and the right timing of trading. The Candlestick lines chart is intuitive, three-dimensional, and contains a large amount of information. It can reflect the basic trend of stock prices and daily stock market fluctuations. Generally, the Candlestick lines in the stock market are sorted together in time series to form a series that reflects the historical changes in the stock price, which is called the Candlestick lines series. [1]

Before the Candlestick lines was applied to the stock market, people used the method of manually identifying the Candlestick lines sequence to make predictions. However, the workload of manual identification is large, and a lot of experience is needed as support. Therefore, the use of intelligent algorithms for predictive analysis has emerged. Financial scientists [3] studied the forecasting capabilities of the Candlestick lines model for different trading methods, and found that short-term Candlestick lines models can be used to obtain benefits. The financier [3] used LSTM to build a forecasting model, tested the forecasting ability of the two-day Candlestick lines model, improved the trading strategy through three factors, and obtained significant results conducive to investment decisions. Financiers [4] analyzed the predictive power of 24 two-day Candlestick lines models for the constituent stocks of the Taiwan 50 Index. They found that the two new models have a strong reversal trend. The financier [5] further researched the profitability of the two-day Candlestick lines model under the holding strategy of buying a bullish (bearish) model and maintaining it until the bearish (bullish) model occurs, and the results were predicted on the São Paulo Stock Exchange in Brazil. Showing all three bullish reversal patterns is profitable. Some financial scientists [6] tested the profitability of the Candlestick lines model under different trend definitions and different holding strategies, and found that the holding strategy is the main factor for the effectiveness of the Candlestick lines analysis. The graph has the ability to predict stock price movements. Financial scientists [7] and others studied the effectiveness of the five-to-two-day candlestick pattern in the Chinese stock market from 1999 to 2009. They found that several bullish and bearish patterns are profitable, but the selected candlestick pattern With strong subjective colors.

Among them, because fuzzy logic is closer to human sensory experience, it has made great progress in recent years. The financier [8] proposed an ordered fuzzy autoregressive model, which introduced an ordered fuzzy number into the stock price prediction, but only considered the linear model, and the Candlestick lines model was mostly non-linear; the financier [9] combined K- The NN algorithm and fuzzy logic have redefined the Candlestick lines model and achieved good returns in the Nasdaq 100 market.

Compared to the analysis results, investors prefer to find the reversal pattern of the stock price rather than predicting the stock price every day. In many cases [10-13] Researchers have focused their efforts on improving the predictions at each moment, but investors are usually only interested in when to buy and sell stocks to make a profit. Based on the above, we propose a method based on fuzzy logic. This method converts Candlestick lines data into understandable rules and patterns for analysis, performs feature learning and classification of Candlestick lines with reverse trends, and makes decisions for investors. stand by.

II. BACKGROUND

A. Candlestick lines Theory

The Candlestick lines chart theory [14-16] comes from the Japanese candle chart theory, which believes that the

978-1-7281-7005-3/20/$31.00 ©2020 IEEE Dalian, China
June 27-29, 2020

Candlestick lines chart model often truly reflects market behavior and people's psychological activities. The K line is composed of the highest price, the lowest price, the opening price and the closing price per unit time. The highest price and the lowest price form a shadow line, and the opening and closing prices of the stock form an entity. In the Shanghai and Shenzhen stock markets, if the opening price is higher than the closing price, the entity is green and called the Yin line; if the opening price of the stock is lower than the closing price, the entity is red, which is called the Yang line. As shown in Figure 1.

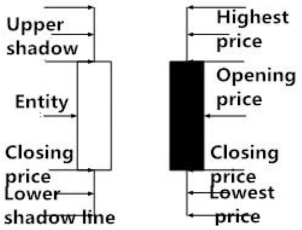

Figure 1. Single-day Candlestick lines chart

B. Fuzzy logic theory

Fuzzy sets [17-19] describe sets without precise quantitative boundaries in real life. A set can represent a concept. A concept and its extension constitute a common set. A concept that can express its extension clearly with a common set can be called a clear concept. A clear concept, either belongs to a set or does not belong to a set, one of the two. However, in real life, not all concepts are clear concepts. For these concepts, ordinary collections are powerless. The fuzzy set [20-22] can describe the set of elements with unclear boundaries in the real world.The general definition of fuzzy sets is as follows:

The fuzzy set A defined in the universal space X is a function defined in X, and the fuzzy set A is written as a pair of $\{x, A(x)\}$ objects.

$$A = \{\{x, A(x)\}\}, x \in X \tag{1}$$

Where x is an element of the universal space X, and A (x) is the value of the function A of that element. The value A (x) is the membership of the elements in the fuzzy set.

III. CANDLESTICK LINES BLURRING

Traditional financial time series analysis is a comprehensive description of the data. However, the Candlestick lines model is a local concept and more reflects information in some special time periods. This information reflects the trend of changes in the time series. However, these valuable models are usually hidden or submerged in a large amount of historical data and cannot be clearly displayed in real time. Therefore, the traditional time series analysis is insufficient in obtaining regular sequence patterns. The research purpose of this article is to find a pattern that reverses the stock price in the Candlestick lines sequence through data mining, so as to provide investors with decision support.

A. Theory of Fuzzy Logic

A reversal refers to a change in the stock price in the stock market in the opposite direction (Figure 2). In this article, the situation where the closing price continues to rise and then fall continuously is defined as the "downward reversal mode"; the situation where the closing price continues to decline and then rises continuously is defined as the "upward reversal mode". It should be noted that continuous ups and downs do not require that the daily Candlestick lines is a positive or negative line in an uptrend or downtrend, which is difficult to appear in real life. Therefore, relaxing the requirements for continuous rises and declines allows a small range of repetitions.

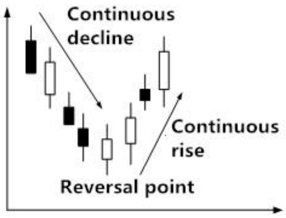

Figure 2. Candlestick lines inversion mode

In the traditional technical analysis, the moving average is used to analyze and determine the trend of the stock price, but it is easy for the situation that the stock price is opposite to the trend of the moving average. In this paper, the central moving average [23] is used instead of the moving average for the judgment of stock price trends. The central moving average is an improvement on the moving average. It takes one of the time points as the center and averages the data multiple times to reduce the impact of different periods on the current period of data.

The calculation method for the centralized moving average CMA_t at time node t is as follows:

$$X_{-t} = \frac{c_{t-3} + c_{t-2} + c_{t-1} + c_t + c_{t+1} + c_{t+2}}{6} \tag{2}$$

$$X_{+t} = \frac{c_{t-2} + c_{t-1} + c_t + c_{t+1} + c_{t+2} + c_{t+3}}{6} \tag{3}$$

$$CMA_t = \frac{X_{-t} + X_{+t}}{2} \tag{4}$$

Where CMA_t is the centralized moving average at time node t; ct is the closing point at t.

The downward trend is defined as follows:

$$CMA(t-6) > CMA(t-5) > \cdots > CMA(t)$$

The uptrend is defined as follows:

$$CMA(t-6) < CMA(t-5) < \cdots < CMA(t)$$

According to the above definition, multiple consecutive reversal points may occur. The article uses the KD indicator for judgment, and the transaction log closest to the upper limit is used as the reversal point.

$$RSV_t = \frac{c_t - l_n}{h_n - l_n} \times 100\% \tag{5}$$

$$K_t = RSV_t \times \frac{1}{3} + K_{t-1} \times \frac{2}{3} \tag{6}$$

$$D_t = K_t \times \frac{1}{3} + D_{t-1} \times \frac{2}{3} \tag{7}$$

Where RSV_t is the original random number on the t trading day, hn, l_n are the highest and lowest stock prices in the last n trading days, and ct is the closing price on the t trading day. If the values of K_t and D_t exceed the upper limit, it means that there is a large difference between ln and c_t, and there is little room for the stock price to rise, and it will soon reach the top of the price in this time range. On the contrary, if the values of K_t and D_t are lower than the lower limit, it means that the difference between ln and c_t is small, and the stock price rises greatly, which may be the bottom of the price in this time range. After determining that the stock price has an upward (downward) trend, determine whether the stock price has the potential to continue to rise (down), which is approximately close to the KD indicator, indicating that the stock has a more reverse trend.

B. Candlestick lines blurring

Order to use this data in a fuzzy manner, a clear time series must be converted into a natural representation that will be used in the fuzzy rules. These rules are evaluated by the size of the Candlestick lines. The stock price conversion to obtain the number of Candlestick lines is defined as follows:

$$b_i = \frac{|o_i - c_i|}{|h_i - l_i|} \tag{8}$$

$$us_i = \begin{cases} \frac{|h_i - o_i|}{|h_i - l_i|}, o_i > c_i \\ \frac{|h_i - c_i|}{|h_i - l_i|}, o_i \le c_i \end{cases} \tag{9}$$

$$ls_i = \begin{cases} \frac{|c_i - l_i|}{|h_i - l_i|}, o_i > c_i \\ \frac{|o_i - l_i|}{|h_i - l_i|}, o_i \le c_i \end{cases} \tag{10}$$

Where b_i represents the K line entity, u_{si} is the K line shadow line, l_{si} is the K line shadow line, and o_i, c_i, h_i, l_i are the K line opening price, closing price, highest price, lowest price, respectively.

The fuzzy sets used to describe the size of the candlestick parts are very short, short, medium, long and very long:

$$\mu_{veryshort}(x) = \begin{cases} 1 - 20x, x \le 0.05 \\ 0, x > 0.05 \end{cases} \tag{11}$$

$$\mu_{short}(x) = \begin{cases} 10x, x \le 0.1 \\ 1, 0.1 < x \le 0.3 \\ 2.5 - 5x, 0.3 < x \le 0.4 \\ 0, x > 0.4 \end{cases} \tag{12}$$

$$\mu_{medium}(x) = \begin{cases} 0, x \le 0.3, x > 0.7 \\ 10x - 3, 0.3 < x \le 0.4 \\ 1, 0.4 < x \le 0.6 \\ 7 - 10x, 0.6 < x \le 0.7 \end{cases} \tag{13}$$

$$\mu_{long}(x) = \begin{cases} 0, x \le 0.5 \\ 5x - 2.5, 0.5 < x \le 0.7 \\ 1, 0.7 < x \le 0.9 \\ 1 - 10x, x > 0.9 \end{cases} \tag{14}$$

$$\mu_{verylong}(x) = \begin{cases} 0, x \le 0.9 \\ 10x - 9, x > 0.9 \end{cases} \tag{15}$$

The physical shape and the length of the shadow line can only determine the shape of the Candlestick lines graphic. In technical analysis, the distance between adjacent Candlestick lines positions also determines the regular information reflected by the Candlestick lines.

Here, the area is defined according to the opening price, closing price, high price, low price, and physical center point of the first k line. Finally, the relative position of the two k lines is defined by the position of the second k line. A, B, C, D, E, F (Figure 3).

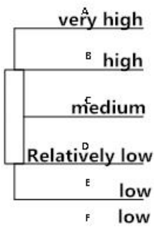

Figure 3. Candlestick lines relative position

IV. EXPERIMENTS AND CONCLUSIONS

A. Experimental data

The Chinese stock market mainly has two securities markets, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The ST sector is a market segment unique to the Chinese stock market. It is a special stock market for companies that have abnormalities in the Shanghai and Shenzhen markets. This article selects the historical transaction data of 100 stocks of SSE A and SZ A stocks as the data set, from January 4, 2017 to January 4, 2019.

TABLE I. STOCK EXAMPLE

Stock code	Stock name
600157	Wing Tai Energy
600022	Shandong Iron and Steel
600166	Foton Motor
600255	Dream Boat
...	...
600653	Shenhua Holdings
600103	Stock historical data

TABLE II. STOCK HISTORICAL DATA

Stock code 600103				
Date	Open price	High price	Low price	Close price
2019/1/4	2.56	2.65	2.55	2.64
2019/1/3	2.58	2.61	2.55	2.58
2019/1/2	2.56	2.62	2.55	2.58
...	...	...	...	...
2018/12/29	3.71	3.75	3.7	3.75
2018/12/28	3.68	3.72	3.66	3.72
...	...	...	...	...
2017/1/5	6.65	7.25	6.56	7.09
2017/1/4	7.75	7.9	6.96	6.99

B. Experimental methods and steps

This paper mainly selects the ID3 algorithm, C4.5 algorithm and support vector machine classification algorithm in the classification algorithm to classify and mine the inversion pattern to verify whether the inversion pattern exists objectively.

The experimental steps are as follows:

The first step is to pre-process the historical data of the original stock and find all points with a reverse trend according to the definition of the uptrend or downtrend. As an example, the training set data A of the A-share market of the Shanghai Stock Exchange uses the closing price to find all points that meet the uptrend or downtrend and mark them. On this basis, the KD index of the five days before and after these points is calculated. The points close to the KD index are regarded as reversal points, marked with "yes" as positive examples, and unsatisfied points as negative examples, marked with "no".

The second step is to extract the opening price, closing price, highest price, and lowest price of the 3rd and 5th days before the reversal point. The five-day Candlestick lines sequence is selected because five days is a trading cycle. According to the definition of fuzzy semantic variables, the Candlestick lines sequence fuzzy method mentioned above is used to fuzzyize the Candlestick lines sequence of the inversion point, that is, the three- and five-day fuzzy Candlestick lines are obtained using these data, including the fuzzy eigenvalues of the Candlestick lines entity and the shadow line length. Entity color, as shown in Tables III and IV.

TABLE III. THREE-DAY CANDLESTICK LINES BLUR CHARACTERISTICS OF LOTUS HEALTH (600186)

k1-b	k1-us	k1-ls	...	k23	class
long	short	long	...	56	no
short	long	long	...	25	no
long	short	short	...	23	no
...	...	...	...	...	...
veryshort	long	verylong	...	46	yes
short	long	long	...	46	no
...	...	...	...	...	...
long	veryshort	short	...	35	no

TABLE IV. FIVE-DAYCANDLESTICK LINES BLUR CHARACTERISTICS OF LOTUS HEALTH (600186)

k1-b	k1-us	...	k4-us	k45	class
short	medium	...	short	23	no
short	medium	...	long	45	no
short	short	...	medium	13	no
...	...	...	...	...	...
long	short	...	long	34	no
short	long	...	veryshort	56	no
...	...	...	verylong	...	...
long	veryshort	...	long	23	no

The third step is to use a decision tree classification algorithm and a support vector machine classification algorithm to perform data classification and mining on the extracted eigenvalues of all the Candlestick lines sequences.

C. Experimental evaluation indicators and results

In this paper, Precision Rate and Recall Rate are used as evaluation indicators. First, the Confusion Matrix is given:

	Was judged as a reversal point	Not judged as a reversal point
Is the true reversal point	A	B
Not the true reversal point	C	D

Among them, A indicates that the algorithm determines that the day is a reversal point and is actually a data sample of the reversal point; B indicates that the algorithm determines that the day is not a reversal point and is actually a data sample of the reversal point; C indicates that the algorithm determines that the day is a reversal point; The turning point is not actually a data sample of the reversal point; D indicates that the algorithm judges that the day is not the reversal point, nor is it actually a data sample of the reversal point.

Accuracy indicates the proportion of correct true inversion points in the prediction of inversion points. The recall rate indicates how many predictions are correct in all the positive samples, that is, the ratio of the accurate inversion points to the total inversion points, that is, the larger the recall rate and accuracy rate, the better. Their calculation formula is as follows:

$$\begin{cases} recall = \dfrac{A}{A+B} \\ precision = \dfrac{A}{A+C} \end{cases} \tag{16}$$

Accuracy and recall are a pair of contradictory indicators. Simply analyzing one of them does not lead to valid conclusions. Therefore, the harmonic mean is used for comprehensive consideration (F-Measure).

$$F = \frac{(1+\alpha^2)rp}{\alpha^2(r+p)} \tag{17}$$

Where r is the recall rate, p is the accuracy rate, α is the weight, and 1 is taken in the text.

Use the inversion mode for classification prediction, and get the prediction results of the inversion mode in the Shanghai Stock A stock training set A as follows:

TABLE V. THREE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET A'S DOWNWARD REVERSAL POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	73.50%	78.10%	75.73%
SVM	79.35%	75.71%	77.48%
C4.5	77.40%	78.70%	78.04%

TABLE VI. FIVE-DAY CANDLESTICK LINES PREDICTION RESULTS OF THE DOWNWARD REVERSAL POINT OF TRAIN

Classification algorithm	recallrate	precisionrate	f-measure
ID3	78.63%	80.14%	79.38%
SVM	83.59%	81.56%	82.55%
C4.5	81.90%	83.00%	82.45%

TABLE VII. THREE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET A UPSIDE DOWN POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	76.86%	79.95%	78.37%
SVM	81.04%	83.73%	82.36%
C4.5	82.68%	77.27%	79.88%

TABLE VIII. FIVE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET A UPSIDE DOWN POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	78.45%	85.63%	81.88%
SVM	85.37%	85.72%	85.54%
C4.5	84.21%	78.29%	81.14%

Use the inversion mode to perform classification prediction, and get the prediction results of the inversion mode in the Shenzhen Stock A training set B as follows:

TABLE IX. THREE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET B'S DOWNWARD INVERSION POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	73.48%	75.24%	74.35%
SVM	76.81%	79.59%	78.18%
C4.5	76.73%	78.12%	77.42%

TABLE X. FIVE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET B'S DOWNWARD INVERSION POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	79.57%	72.63%	75.94%
SVM	79.53%	83.41%	81.42%
C4.5	83.76%	76.41%	79.92%

TABLE XI. THREE-DAY CANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET B UPSIDE DOWN POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	79.58%	71.72%	75.45%
SVM	76.98%	71.75%	74.27%
C4.5	75.48%	80.57%	77.94%

TABLE XII. FIVE-DAYCANDLESTICK LINES PREDICTION RESULTS OF TRAINING SET B UPSIDE DOWN POINT

Classification algorithm	recallrate	precisionrate	f-measure
ID3	86.31%	81.26%	83.71%
SVM	82.67%	85.47%	84.05%
C4.5	71.26%	78.26%	74.60%

From the table, it can be concluded that in the Shanghai Stock A training set and Shenzhen Stock A training set, the reverse model classification prediction recall rate basically exceeds 73%, and the accuracy rate reaches 75%, indicating that the reverse mode is real. At the same time, the accuracy and recall of the five-day fuzzy Candlestick lines is higher than the three-day fuzzy Candlestick lines in the classification of the forward-reversed point and the downward-reversed point classification prediction. The line has better effect.

By comparing the Piecewise Linear Representation model, artificial labeling and the fuzzy logic representation proposed in this paper, the experimental results are shown to verify the feasibility of the method in this paper. Except that the sample inversion mode labeling method is different in the experiment, other conditions are consistent, and the support vector machine classification prediction method is used. The adopted trading rules are as follows: the data on day t is used to predict the trading decision (buy, sell, position) on day t+1. The trading decision is made when the market opens on day t+1, and no buy occurs The decision signal (upward reversal signal) buys a fixed amount of stocks. When the sell decision signal (downward reversal signal) appears, all the stocks currently held are sold. For a period of time, the total asset investment return on stock transactions is as shown in the formula.

$$Rate=\{\sum_{i=1}^{k}\frac{[(1-tax-charge)\times sell_i-(1+tax)\times buy_i]}{[(1+tax)\times buy_i]}\} \times 100\%, i=1,2,3,\ldots,k \qquad (18)$$

Among them, tax is the tax rate; charge is the handling fee in the stock transaction; k is the number of transactions; $sell_i$ is the selling price of the stock in the i transaction; buy_i is the buying price of the stock in the i transaction.

Data of Lotus Health (stock code: 600186) from January 4, 2017 to January 4, 2019 were obtained as historical transaction data, and data from January 4, 2017 to June 4, 2018 were used as test set data.

The optimal parameter of the cost-sensitive support vector machine obtained through parameter optimization in the experiment is to select the RBF kernel function. By predicting the test set $C=0.79$, $gamma=1.05$, the return on experimental investment is shown in Table XIII.

The data of Nanshan Aluminum (stock code: 600219) from January 4, 2017 to January 4, 2019 was obtained as historical transaction data, and the data from January 4, 2017 to June 4, 2018 was used as test set data.

TABLE XIII. COMPARISON OF LOTUS HEALTH FUZZY LOGIC REPRESENTATION, ARTIFICIAL MARKING, AND PIECEWISE LINEAR REPRESENTATION

		Fuzzy logic notation	Artificial marking	Piecewise linear representation
Expected buy result precision	precision	78.81%	65.28%	55.13%
	recall	80.65%	73.47%	58.96%
Expected selling result precision	precision	76.93%	77.12%	59.27%
	recall	79.65%	70.86%	61.13%
Return rate		43.87%	39.54%	31.66%

TABLE XIV. COMPARISON OF FUZZY LOGIC REPRESENTATION, ARTIFICIAL MARKING AND PIECEWISE LINEAR REPRESENTATION OF NANSHAN ALUMINUM

		Fuzzy logic notation	Artificial marking	Piecewise linear representation
Expected buy result precision	precision	81.27%	71.37%	59.51%
	recall	76.85%	74.70%	58.49%
Expected selling result precision	precision	79.31%	70.34%	58.17%
	recall	77.56%	72.59%	56.35%
Return rate		38.03%	31.47%	19.96%

It can be seen from the above table that the reversal pattern is real and can guide investors to invest. Compared with piecewise linear representation, fuzzy logic can more effectively mine inversion patterns in Candlestick lines sequences, and at the same time, the return on investment has been greatly improved.

V. CONCLUSION

The classification model of stock reversal pattern based on fuzzy Candlestick lines proposed in this paper is an analysis model of stock market early warning technology. This model applies central moving average to stock price trend analysis and fuzzy logic theory to traditional Candlestick lines analysis techniques. Find the point where the stock price has a reversal trend through the central moving average, and based on this, convert the opening, closing, high, and low prices in the Candlestick lines into a fuzzy Candlestick lines. Classify and study the Candlestick lines pattern before the reversal point, and then obtain the fuzzy Candlestick lines reversal pattern recognition method to further predict the fuzzy Candlestick lines reversal pattern. This paper chooses to conduct empirical research in the two stock markets of Shanghai Stock A and Shenzhen Stock A. The experimental results show that the fuzzy Candlestick lines reversal pattern proposed in this paper can be better identified. At the same time, compared with the traditional piecewise linear representation method, it is better to mine the inversion pattern in the Candlestick lines sequence. Under the same conditions, the return on investment has improved to a certain extent.

REFERENCES

[1] Zhang X, Zhang Y, Wang S, et al. Improving Stock Market Prediction via Heterogeneous Information Fusion . Papers, 03, 1, 2018, pp.45-51.

[2] Ren L, Ren P, Glasure Y. On the different forms of returns from moving average buy-sell trading rule in the Stock Market. Benchmarking An International Journal, 25, 1, 2018, pp.05-14.

[3] Nelson D M Q, Pereira A C M, Oliveira R A D. Stock market's price movement prediction with LSTM neural networks 2017 International Joint Conference on Neural Networks (IJCNN). IEEE, 2017.

[4] T.H. Lu, Y.M. Shiu, Tests for two-day candlestick patterns in the emerging equity market of Taiwan, Emerg. Market. Finance Trade, 28, 2012, pp.39 – 55.

[5] Malagrino L S, Roman N T, Monteiro A M. Forecasting Stock Market Index Daily Direction: a Bayesian Network Approach . Expert Systems with Applications,04,01,2018, pp.105-117.

[6] T.H. Lu, Y.C. Chen, Y.C. Hsu, Trend definition or holding strategy: What determines the profitability of candlestick charting? J. Bank. Finance, 6, 1,2015, pp.172 – 183.

[7] M. Zhu, S. Atri, E. Yegen, Are candlestick trading strategies effective in certain stocks with distinct features Pac.-Basin Finance J. (2015).

[8] Kamo T, Dagli C. Hybrid approach to the Japanese candlestick method for financial forecasting. Expert Systems with Applications, 36, 2009, pp.5023-5030.

[9] MarszaEk A, Burczyński, T. Modeling and forecasting financial time series with ordered fuzzy candlesticks. Information Sciences, 27, 3,2014, pp.144-155.

[10] Naranjo R, Santos M. Fuzzy Candlesticks Forecasting Using Pattern Recognition for Stock Markets,7,2016, pp.154-160.

[11] Asadifar S, Kahani M. Semantic association rule mining: A new approach for stock market prediction // Swarm Intelligence & Evolutionary Computation. IEEE, 2017.

[12] Peker S, Aktan B, Tvaronaviciene M. Clustering in Key G-7 Stock Market Indices . Social Science Electronic Publishing, 14,05,2017, pp.31-42.

[13] Lu Tao, Hao Yongtao. Stock price prediction based on K-line sequence similarity search. Journal of Computer Applications, 37,2,2017, pp.234-240.

[14] Lu Tao, Hao Yongtao. Study on profitability of K-line pattern based on similarity matching and clustering . Computer Science,03,2018, pp.7-9+33.

[15] Chen Qi'an, Lei Xiaoyan. Monetary policy, investor sentiment and volatility of China's stock market: theory and empirical research. China Management Science,25,11,2017, pp.56-63.

[16] Rao Dongning, Guo Haifeng, Jiang Zhihua. Simulation of Stock Index Based on Parallel Probabilistic Programming. Chinese Journal of Computers,6,2019, pp.1334-1350.

[17] Fan Jianping, Yan Yan, Wu Meiqin. Multi-criteria decision-making method based on triangular Pythagorean fuzzy set . Control and Decision,8,2019, pp.1601-1608.

[18] Yan Feifei, Wei Cuiping, Ren Zhiliang. Entropy of Hesitant Fuzzy Sets . Mathematics in Practice and Theory,14,2018, pp.117-131.

[19] Xue Huiling, Chen Chunfang. Hesitant fuzzy set distance considering deviation degree and its application in pattern recognition. Statistics and Decision,34,19,2018, pp.397-412.

[20] Pei Pei, Yuan Xuehai. Interval Entropy and Interval Similarity of Interval Intuitionistic Fuzzy Sets . Fuzzy Systems and Mathematics, 6,2018, pp.141-149.

[21] Fan Yanhuan, Li Yongming. Achievability of Fuzzy Linear Sequential Logic. Chinese Journal of Electronics, 5, 2018, pp.781-795.

[22] Pei Daowu. A Review of Ten Years Research on the Basic Issues of Fuzzy Logic and Fuzzy Reasoning Logic. Journal of Engineering Mathematics, 5,4,2010, pp.27-35.

[23] Zhang Yayun, Wu Qunying. Precise Asymptotic Properties of Complete Moment Convergence for Φ -Mixed Moving Average Process. Journal of Jilin University Science Edition, 1,2017 pp.48-56.