Modeling Candlestick Patterns with Interpolative Boolean Algebra for Investment Decision Making

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Abstract. In this paper we present one way of modeling candlestick patterns using interpolative Boolean algebra (IBA). This method shows a degree of fulfillment for observed patterns, thus giving traders easy interpretation of by how much candlesticks fit into different patterns. Candlestick patterns have been used for financial forecasting for a couple of decades on Western markets and they have become a mainstream trader's tool. Since the need for automated candlestick patterns discovery arose, some papers proposed fuzzy approach as a solution. Our decision to use IBA for modeling candlestick patterns comes from the fact that fuzzy logic has it limits and cannot be applied to these models. Proposed method is another approach to the same problem, but it could not be modeled using conventional fuzzy logic, because it is necessary for it to be in the Boolean frame. Results obtained from our tests are satisfactory and also open the opportunity for combining this technique with existing ones.

Keywords: interpolative Boolean algebra, real valued logic, candlestick patterns, financial forecasting.

1 Introduction

Usage of candlestick patterns as financial indicators has been defended and disputed in literature during the last decade. They prove to be useful on some markets and shown unprofitable on others. The fact is that candlestick patterns were invented for rise markets during the second half of the 1700s and some conclude that they are not suitable for today markets [9]. Anyhow, fact is that traders use this kind of technical analysis on an everyday basis. It is supposed to reveal emotional beliefs of traders on the market, since they too affect the price [10]. This kind of behaviour is not completely rational, and technical analysis transforms thought process of investors into charts in an effort to forecast the price change.

Models are individual for each trader, so there is no optimal solution to this problem. Instead, methodology that can help traders to express their personal preferences is needed. Emerging papers in scope of candlestick patterns show an uprising interest

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in imprecise modelling. Many of these papers show respectful results. Since conventional fuzzy logic does not treat consistently all logical relations, using it for proposed models is not satisfactory. To address this problem, interpolative Boolean algebra is introduced to candlestick modelling.

For defining candlestick patterns, method proposed in this paper uses interpolative Boolean algebra as a consistent fuzzy technique [11]. Conventional fuzzy approach is hindered by the fact that it cannot consistently describe elements of Boolean algebra and stay in a Boolean frame [14]. One occurrence is for instance the law of contradiction ($A \cap \overline{A}$). Therefore, proposed models cannot be implemented with traditional fuzzy approach. IBA or consistent fuzzy technique, as it is sometimes referred in literature, must be applied to improve upon strongly set conventional fuzzy logic.

For test purposes we used random data interval from a stock market. Our results reveal that transforming candlestick parameters, by using proposed methodology, into intensity of a candlestick pattern, truly mimics human perception.

The rest of the paper is organized into four sections. Section 2 analyses contemporary literature, in section 3 data and methodology are described, results are explained in section 4 and the last section concludes the paper.

2 Literature Review

Effectiveness of Japanese candlestick patterns on stock and similar markets is perpetually re-examined. There are papers which suggest that usage of such patterns for forecasting on stock markets is unjustified. For instance, studies conducted in [1] and [9] show that candlestick patterns as a type technical analysis do not produce profit. In [9] authors used thirty-five individual stock indexes with carefully chosen sample period of ten years. Robustness of the system was tested using the bootstrap methodology. One of the criticisms was addressed to the fact that candlestick patterns were originally devised for rice markets.

In contrast, recent study conducted in [8] shows that some types of candlestick technical analysis patterns are indeed profitable when applied to Taiwan stock market. Data used for testing this method comprised of individual stocks found in Taiwan 50. To check the robustness of results, again, bootstrap methodology was used. Despite the fact that some of these results put shadow onto candlestick patterns effectiveness, many papers have been written regarding their usage in forecasting.

Research presented in [7] created an expert system based on candlestick chart analysis. Their system looks up in a database for signals and interprets them as candlestick patterns. They get 72% accurate results on the Korean stock market. The model is rule-based.

Tool which uses fuzzy candlestick patterns to describe investment knowledge on the Taiwan stock market was presented in [5]. By using fuzzy technique, they are addressing the problem of candlestick pattern definition vagueness which arises from different authors' comprehensions of the same pattern. In another paper, group of same authors compare their method with previously presented ones, acquiring better results [6]. Finally, in [4] Lee constructs personal ontology to describe candlestick patterns.

Approaches presented in [2] use candlestick method in gating network, by using rules for describing the market and also by fuzzy logic-based weight generator, as part of their hybrid system. As they have shown, fuzzy logic based systems deliver smoother and more accurate forecasting results. Another fuzzy-candlestick model for reversal point prediction was presented in [3]. It tries to set a warning before a reversal of a stock price occurs. Reported results show precision far greater than 50%.

3 Data and Methodology

The origin of candlesticks dates from the mid-18th century, and was firstly introduced by a youngest child of Munehisa family named Homma [10]. From his excellence in the field of trading, people started calling him “god of the markets”. After Nison introduced Japanese candlestick trading techniques to western markets, they rapidly gained popularity. Today, candlesticks chart analysis is widely used type of technical analysis. Candlestick patterns should reflect psychological state of the market and traders should be able to base their decisions upon recognized patterns.

Candlesticks are formed out of the open, high, low and close price for a predefined time period Fig. 1. Body color of a candlestick depends on whether the close price is higher or lower than the open price. If it is higher, body usually has a white or an empty filling and oppositely, if it is lower, body is black or filled. Lines called shadows above and under body represent highest and lowest price of the time interval, respectively. Body size indicates the market momentum and the shadows show extremes of the price movement. Body and shadows are usually described as long or short.

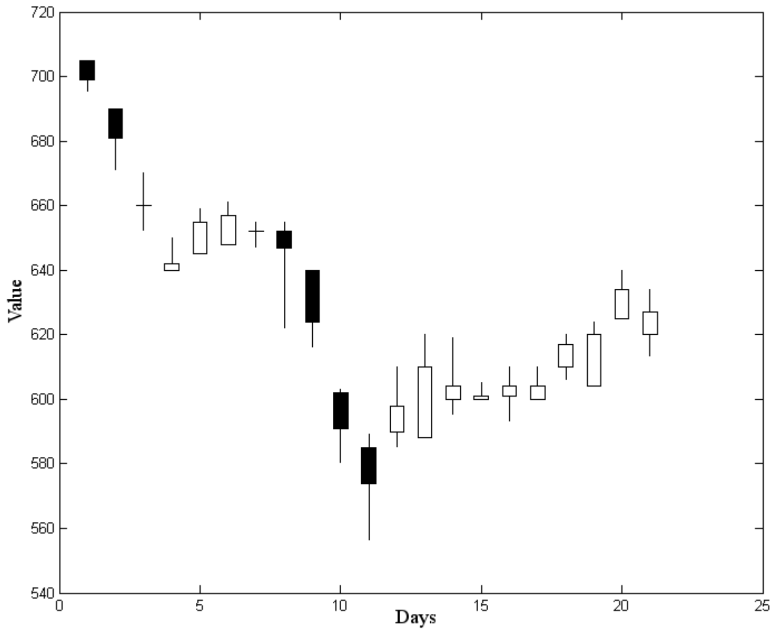

Fig. 1. Candlestick examples

The way a candlestick can reflect the market state can be given with the following example. Candle with white body without shadows is called the White Marubozu pattern. Open price equals lowest price, and close price equals the highest. That means buyers are very bullish, since market opened at one price and closed at another, and the price never dropped below initial price, and it closed well above it. The opposite rule applies for black body, Black Marubozu.

Interpretation of candlestick patterns is individual. Investors can obtain different pieces of information from the same pattern and apply custom set of rules. To make the modeling possible, we use interpolative Boolean algebra. With this consistent fuzzy technique we are able of modeling vagueness of candlestick patterns recognition. This new approach simplifies pattern definition, making it easier for investors to use. Usage is straightforward and only basic mathematical skills are required. Need for gradation is also satisfied, for instance we can calculate how intensive White Marubozu is. This provides information about certainty that the pattern emergence will reflect the future market movement.

3.1 Candlestick Fuzzy Modeling

Since idea behind imprecise or fuzzy modeling of candlesticks is already being explored in literature, we will first shortly explain approach presented in [4, 5, and 6]. To describe a candlestick line in an imprecise manner as long, middle or short, four linguistic variables are defined: EQUAL, SHORT, MIDDLE and LONG. They indicate fuzzy sets of shadows and body length. Membership function μ(x) of linguistic variables is described on Fig. 2.

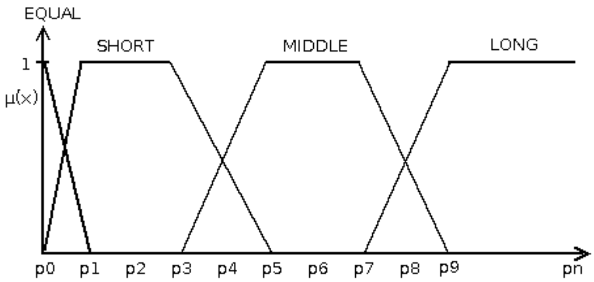

Fig. 2. Fuzzy sets of shadows and body length

Values are set from p_0 to p_n, depending on the maximum percentage change of observed time series per interval. For example, on TAIEX values should range from 0 to 14 since they can only change so much per day interval. X-axis is a real value of body or shadow. Input values for membership functions can be calculated with following equations:

$$
\begin{aligned}
L_{upper\_shadow} &= \frac{high - \max(open, close)}{open} \times 100 \\
L_{lower\_shadow} &= \frac{\min(open, close) - low}{open} \times 100 \\
L_{body} &= \frac{high - \max(open, close)}{open} \times 100.
\end{aligned} \tag{1}
$$

Those input values are comparable to the values later presented as the percentage limits normalization explained later. Also, additional calculations should be made for the determination of body type. There are three states of the body: BLACK, WHITE and CROSS. The last-mentioned is the situation where body has the 0 size or in another words open equals close price. Additional set of rules is defined as follows:

$$
\begin{aligned}
&IF\ open - close > 0\ THEN\ \text{body is BLACK} \\
&IF\ open - close < 0\ THEN\ \text{body is WHITE} \\
&IF\ open - close = 0\ THEN\ \text{body is CROSS.}
\end{aligned} \tag{2}
$$

Multiple candlestick relations are modeled in the same sense, by defining five linguistic variables to represent open style relations and five for close style. Fuzzy modifiers and trend modeling is also introduced. Complete procedure is described in [6].

3.2 Candlestick Modeling with Interpolative Boolean Algebra

IBA requires for all values to be on the [0,1] interval. Candlestick values must be normalized taking those rules into consideration. If we know maximal possible price change, it could be better to treat extreme movements with higher degree. For instance on TAIEX, the upward movement of 7% can be considered as 1 and downward movement of 7% as 0. The problem is that near border movements are really scarce and with this kind of normalization normalized candlesticks would be too small for IBA to properly treat them. Also, with this kind of normalization, all open prices are set to a fixed value. In case where symmetrical maximal and minimal price changes are to be expected, that is the 0.5 value, otherwise it is some other. That means that data of relative position between candlesticks is lost. One solution for this problem is min-max normalization performed on the whole data set. However, this will not address the first problem. Another option is to normalize groups of elements that create a single pattern. This way, relevant bars will maintain their relations. It is clear that there is no single solution for every problem, so type of normalization should be chosen according to specific needs. Aggregation of two or more differently normalized data sets should also be considered. For example purposes in this paper, we used min-max normalization on pattern groups since there are no disadvantages of using it on selected cases.

In [11] is presented [0,1]-valued logic that is in the Boolean frame. This gives us the opportunity to use consistent fuzzy relations or interpolative relations [12], to measure logical similarity and dissimilarity between individuals. Interpolative Boolean algebra provides a frame for consistent realization of all possible elements of finite Boolean algebra. It is consistent in a sense that it preserves all the laws on which Boolean algebra relies.

In this paper classical Boolean expressions are used for modeling candlestick patterns. As an example, a few expressions have been described. Equivalence is used when we want to state that parameters are equal. Relation of equivalence (⇔) is well-known expression of logical similarity between objects. Equivalence of two objects A and B is noted as:

$$A \Leftrightarrow B = (A \cap B) \cup (\overline{A} \cap \overline{B}). \tag{3}$$

For Doji pattern open equals close price so it can be defined with ease by stating open⇔close.

If we do not want attributes to be the same, logical choice of an operator is exclusive disjunction ($\underline{\vee}$). Relation of exclusive disjunction is complementary relation to the equivalence relation:

$$A \underline{\vee} B = 1 - \left(A \Leftrightarrow B\right) = (A \cap \overline{B}) \cup (\overline{A} \cap B). \tag{4}$$

Long day pattern can be modeled as an exclusive disjunction between open and close price. It can be expressed as close and open prices as far apart as possible.

Maximal value for relation of exclusive disjunction between open and close price is obtained when open and close prices have extreme but different values. For instance open price has a value of 1 and close price has a value of 0.

Very useful expression is implication ($\rightarrow$). It can be viewed as a non-strict inequality relation, or simplified less or equals ≤.

$$A \rightarrow B = (\overline{A} \cup B). \tag{5}$$

For instance, this expression can be used for defining the Engulfing pattern which is described as a candlestick with a small body which is engulfed by a bigger body of the next bar.

Because there relations are based on interpolative Boolean algebra (IBA), which is real-valued [0,1]-valued realization of finite Boolean algebra [13] we need to find their generalized Boolean polynomial. Any element from the IBA has its corresponding generalized Boolean polynomial (GBP) [14].

Transformation from Boolean expressions to GBP is described and the example of the process for exclusive disjunction is given by the following expression:

$$\begin{aligned}(A\underline{\vee}B)^{\otimes} &= [(A\cap\overline{B})\cup(\overline{A}\cap B)]^{\otimes}\\ &= (A\cap\overline{B})^{\otimes}+(\overline{A}\cap B)^{\otimes}-(A\cap\overline{B})^{\otimes}\otimes(\overline{A}\cap B)^{\otimes}\\ &= A\otimes(1-B)+(1-A)\otimes B-[A\otimes(1-B)]\otimes[(1-A)\otimes B]\\ &= A+B-2(A\otimes B).\end{aligned} \tag{6}$$

Generalized product ($\otimes$) is any function that satisfies conditions of commutativety, associativity, monotonicity, 1 as identity and non-negativity condition:

$$\otimes:[0,1]\times[0,1]\to[0,1]. \tag{7}$$

If both attributes have the same type, we can use minimum t-norm as a generalized product. That would mean they are correlated. For instance, if we compare two persons by their height, intersection of their heights is smaller person's height. If attributes are non-correlated, product t-norm should be used instead. An example of this is if compare two persons by their height and their wealth. At last, if they are negatively correlated Łukasiewicz t-norm should be used.

Example above (6) can now be transformed to:

$$(A\underline{\vee}B)^{\otimes}=A+B-2(A\otimes B)=A+B-2\min(A,B). \tag{8}$$

Next, example models for candlestick patterns are given. This should illustrate how fuzziness can help in determining the intensity and avoid completely discarding candlestick patterns that only on small part do not satisfy conditions.

White Marubozu:

$$open\Leftrightarrow low \quad\wedge\quad close\Leftrightarrow high. \tag{9}$$

Doji:

$$open\Leftrightarrow close. \tag{10}$$

Hammer:

$$close\Leftrightarrow high \quad\wedge\quad open\underline{\vee}low. \tag{11}$$

Bullish Engulfing:

$$high1\to close2\wedge open2\to low1\wedge close2\to open2. \tag{12}$$

Variables high1 and low1 represent high and low prices of preceding candlestick and open2 and close2 open and close prices about the latter. Last part says that close price should be smaller than the open price of the second candlestick.

4 Results

Tests show that candlestick patterns modelled using IBA can provide good representation of how human traders percept market movements. For traders this means a significant help since they do not have to monitor changes personally, but instead just wait for signals when a pattern is formed. This can further automate the process, since traders can create rules on which when event is triggered actions could be taken automatically. IBA can also be used for automation as a logical aggregation tool.

In this section, we will compare how models are defined using IBA and fuzzy approach. For instance, we will compare Bullish Engulfing model presented in [4] with ours (12). For the sake of simplicity, previous trend information is omitted.

One needs to define all attributes using linguistic variables in fuzzy approach. Since we have two candlesticks composing this pattern we need information about open style, close style, upper shadow, body size, body colour and lower shadow for both candlesticks. This gives great flexibility in defining patterns and is further supported by possibility to custom-tailor membership function. Rules can be expressed as (13).

$$\begin{aligned}
&IF\ line1_open_style = OPEN_LOW \\
&AND\ line1_close_style = CLOSE_HIGH \\
&AND\ line1_body_size = LONG \\
&AND\ line1_body_color = WHITE \\
&AND\ line2_open_style = OPEN_HIGH \\
&AND\ line2_close_style = CLOSE_LOW \\
&AND\ line2_body_size = SHORT \\
&AND\ line2_body_color = BLACK.
\end{aligned} \tag{13}$$

Our approach was already described with (3.12). It is straightforward and all tweaking has to be done using logical expressions. With (3.12) it is described that high price of previous candlestick is smaller than the close price of the following one and that low price of the first one is above the value of the second candlestick open price. Last part of the expression shows that body of the first candlestick should be black. In other words, first candlestick is completely engulfed by the body of a following candlestick and is bearish.

Next part presents some usage cases. Only one bar candlestick patterns are used in the example Fig. 3. Table 1 contains data on which Fig.4.1 charts are made.

Some described models (9-12) are very rough and could use some improvement. Obviously, Marubozu pattern is not complete, since by this definition candlestick is recognized as Marubozu even when Doji without shadows occurs. One way of improving Marubozu model is to compare it with Doji. Since there is no ambiguity in definition of the Doji pattern, we can use it to improve upon other models. For instance, Marubozu is Marubozu, only when it is not a Doji. Marubozu model described by (9) can have high intensity even when Doji appears. Maybe it is correct to treat it in such a way in some cases, but traders would probably dismiss Marubozu if it does not have larger body. That leaves us with at least two options. One is to look for Marubozu when Doji does not occur and the other is to look for Marubozu when Doji is described as less intensive.

The first scenario, White Marubozu and not Doji, depicts traders who consider that Marubozu patterns cannot occur unless body has the opposite size of an ideal Doji body size. Second scenario, White Marubozu larger than Doji, is less harsh and the condition is met when Doji's intensity is smaller than the one of Marubozu. It is interesting to note that both scenarios give very similar results, but the latter one, case with the converse implication between indicators, is more tolerant. It also appears shifted up compared to the first scenario.

Results depend on type of normalization chosen. For Hammer, if data are normalized using min-max for each bar, we get redundant calculations left and right from $\wedge$. But, if we choose some other type of normalization, results will change accordingly.

For data presented in Table 1 and Fig. 3 we used min-max normalization on each candlestick. If min-max normalization on the whole interval was used, results would be different. In this example, most notable difference is how logical relations influence changes. Sheffer stroke between White Marubozu and Doji will almost never produce maximal intensity. If converse implication is used, Doji has very little influence on White Marubozu.

Table 1. Original data and IBA modelling results

Open	High	Low	Close	White Marubozu	Dodji	Marubozu $\wedge \neg$ Dodji	Marubozu $\leftarrow$ Dodji
515	519	510	515	0,4444	1,0000	0,0000	0,4444
510	515	510	513	0,6000	0,4000	0,3600	0,8400
519	534	517	522	0,2941	0,8235	0,0519	0,4187
524	549	524	538	0,5600	0,4400	0,3136	0,8064
550	592	550	590	0,9524	0,0476	0,9070	0,9977
584	590	570	580	0,3000	0,8000	0,0600	0,4400
590	638	590	621	0,6458	0,3542	0,4171	0,8746
630	683	630	675	0,8491	0,1509	0,7209	0,9772
743	743	720	740	0,0000	0,8696	0,0000	0,1304
777	788	730	771	0,1897	0,8966	0,0196	0,2735
731	735	709	722	0,1538	0,6538	0,0533	0,4467
672	740	672	711	0,5735	0,4265	0,3289	0,8181
722	759	722	750	0,7568	0,2432	0,5727	0,9408
515	519	510	515	0,4444	1,0000	0,0000	0,4444

As generalized product in GBP for Doji and Marubozu we use minimum t-norm, since all inputs have the same nature. But, for relations between candlesticks, we use product t-norm. In situations where the proposed method needs more tuning, pseudo-logical polynomial can be used to introduce weights [15].

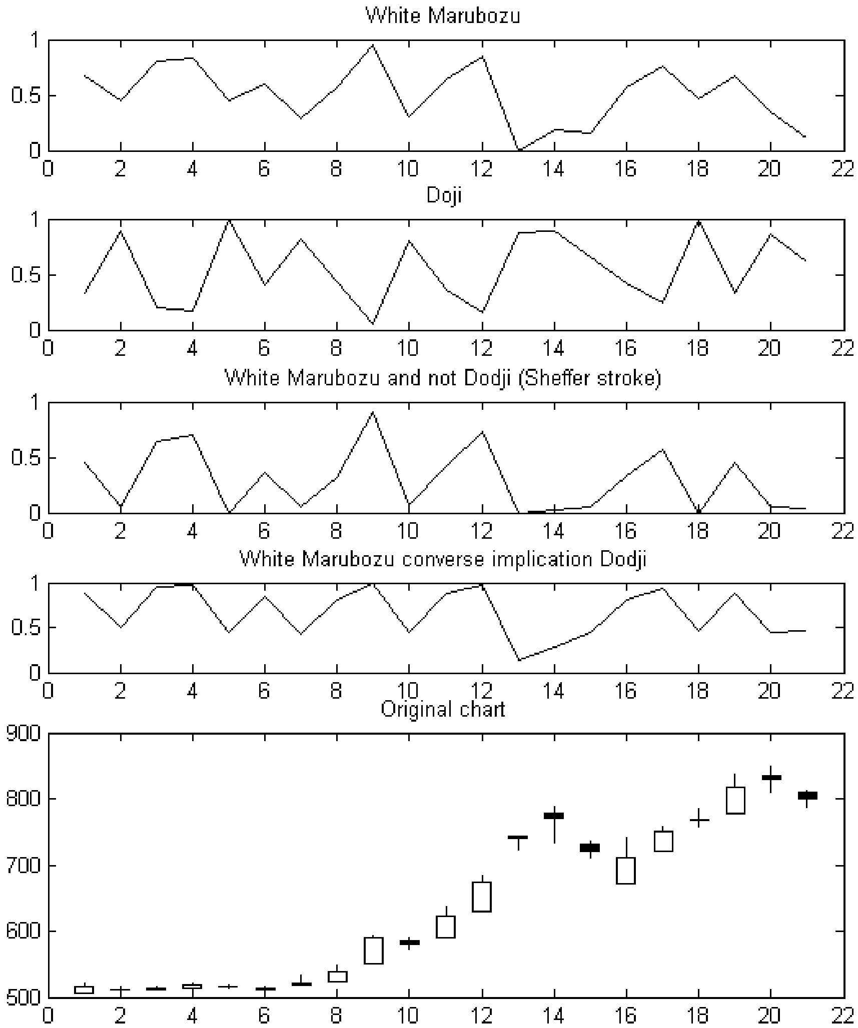

Fig. 3. IBA White Marubozu and Doji results

5 Conclusion

In this paper we wanted to introduce IBA to candlestick patterns modelling. By using proposed method it should be easy for traders to model their ideas of candlestick patterns, whether simple or complex. In the results section we have shown that our approach is indeed successful. By using this technique it is also possible to incorporate other methods of candlestick patterns modelling. To our best knowledge this is the first paper to address candlestick patterns modelling using IBA.

Previous studies used conventional fuzzy logic to model candlestick patterns, and have shown very good results. The most notable void in this approach is arising model complexity, when more patterns should be aggregated in one new pattern. The approach in this paper on the other hand, lacks the ability to directly describe attributes with linguistic variables, but rather it uses relations between them. Once modeled, candlestick patterns can be simply put in any relation.Our methodology uses basic logic expressions to model everything from candlestick patterns to custom candlestick related indicators and then uses IBA to translate these expressions into values.

We believe that this new approach will give more flexibility in candlestick pattern modelling, which would in return give better support in investment decision making.

References

1. Horton, M.J.: Stars, crows, and doji: The use of candlesticks in stock selection. The Quarterly Review of Economics and Finance (2009), doi:10.1016/j.qref.2007.10.005
2. Kamo, T., Dagli, C.: Hybrid approach to the Japanese candlestick method for financial forecasting. Expert Systems with Applications (2009), doi:10.1016/j.eswa.2008.06.050
3. Lan, Q., Zhang, D., Xiong, L.: Reversal Pattern Discovery in Financial Time Series Based on Fuzzy Candlestick Lines. Systems Engineering Procedia (2011), doi:10.1016/j.sepro.2011.10.021
4. Lee, C.-H.L.: Modeling Personalized Fuzzy Candlestick Patterns for Investment Decision Making. IEEE Computer Society (2009), doi:10.1109/APCIP.2009.207
5. Lee, C.-H.L., Chen, W., Liu, A.: Candlestick Tutor: An Intelligent Tool for Investment Knowledge Learning and Sharing. IEEE Computer Society (2005), doi:10.1109/ICALT.2005.82
6. Lee, C.-H.L., Liu, A., Chen, W.-S.: Pattern Discovery of Fuzzy Time Series for Financial Prediction. IEEE Transactions on Knowledge and Data Engineering (2006), doi:10.1109/TKDE.2006.80
7. Lee, K.H., Jo, G.S.: Expert system for predicting stock market timing using a candlestick chart. Expert Systems with Applications (1999), doi:10.1016/S0957-4174(99)00011-1
8. Lu, T.-H., Shiu, Y.-M., Liu, T.-C.: Profitable candlestick trading strategies—The evidence from a new perspective. Review of Financial Economics (2012), doi:10.1016/j.rfe.2012.02.001
9. Marshall, B.R., Young, M.R., Rose, L.C.: Candlestick technical trading strategies: Can they create value for investors? Journal of Banking & Finance (2006), doi:10.1016/j.jbankfin.2005.08.001
10. Nison S.: Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East. New York Institute of Finance, USA (1991)
11. Radojevic, D.: New [0,1]-valued logic: A natural generalization of Boolean logic. Yugoslav Journal of Operational Research - YUJOR 10(2), 185–216 (2000)
12. Radojevic, D.: Interpolative Relations and Interpolative Preference Structures. Yugoslav Journal of Operational Research - YUJOR 15(2), 171–189 (2005)
13. Radojevic, D.: Interpolative Realization of Boolean Algebra as a Consistent Frame for Gradation and/or Fuzziness. Forging New Frontiers: Fuzzy Pioneers (2008), doi:10.1007/978-3-540-73185-6_13
14. Radojevic, D.: Fuzzy Set Theory in Boolean Frame, Workshop invited key lecture. International Journal of Computers, Communications & Control 3, 121–131 (2008)
15. Radojevic, D.: Logical Aggregation Based on Interpolative Boolean Algebra. Mathware & Soft Computing 15(1), 125–141 (2008)