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Przemysław Juszczuk*
Lech Kruś**

SUPPORTING MULTICRITERIA FUZZY DECISIONS ON THE FOREX MARKET

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Abstract

This paper deals with decisions made by a decision maker using technical analysis on the Forex market. For a number of currency pairs on the market the decision maker obtains buy or sell signals from transaction systems using technical analysis indicators. The signal is generated only when the assumed conditions are satisfied for a given indicator. The information characterizing every market situation and presented to the decision maker is binary: he either obtains the signal or does not.

In this paper a fuzzy multicriteria approach is proposed to extend and valuate information for the analysis of the market situation. The traditional approach with binary characterization of the market situations, referred to as a crisp approach, is replaced by a fuzzy approach, in which the strict conditions for which the crisp signal was generated are fuzzy. The efficiency of a given currency pair is estimated using values from the range $\langle 0, 1\rangle$ and is defined by the membership function for each technical indicator. The values calculated for different indicators are treated as criteria. The efficiency of a given currency pair can be analyzed jointly for several indicators. The currency pairs are compared in the multicriteria space in which domination relations, describing preferences of the decision maker, are introduced. An algorithm is proposed which generates Pareto-optimal variants of currency pairs presented to the decision maker. The method proposed allows to extend the number of analyzed currency pairs, without significantly increasing the computation time.

* University of Economics in Katowice, Faculty of Informatics and Communication, Department of Knowledge Engineering, e-mail: przemyslaw.juszczuk@ue.katowice.pl.

** Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland, e-mail: Lech.Krus@ibspan.waw.pl.

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1 Introduction

The Forex market is a global, decentralized currency market. It is regarded as the most liquid market in the world, and its daily turnover, even in the local currencies, often reaches trillions of dollars (McLeod, 2014). A currency pair is the basic instrument used on the Forex market; it can be regarded as the ratio of one currency to another. Thanks to four overlapping sessions, the Forex market has high accessibility even for retail clients. The ease of access to trading tools makes the Forex market very popular. Nowadays, such notions as technical analysis (which includes trend indicators, oscillators, Fibonacci levels, Pivot points and more), along with fundamental analysis, are crucial components of rule-based trading systems, in which easily understandable signals are used to open trading positions.

A rule-based trading system can be regarded as a set of rules related to technical analysis indicators or candle formations which are transformed into trading signals. Nowadays there is a growing tendency, in which these concepts are included in various complex systems based on neural networks (Yao et al., 2000; Lai et al., 2005), evolutionary prediction (Slany, 2009), evidence theory (Liu et al., 2009) and more. While fuzzy sets are also used in these methods (Kablan, 2009), many papers deal with multi-agent systems (Barbosa et al., 2008). Notions from AI systems (Yu et al., 2005) along with evolutionary computation (Hirabayashi et al., 2009) are intensively developed. Papers on fundamental analysis (like Nassirtoussi et al., 2015) included in the trading systems are less common that those including the technical analysis.

Nowadays there is no agreement about the efficiency of technical analysis. The same can be stated for rule-based trading systems. The number of papers dealing with the optimization of technical indicators remains high, while such papers as Cheol-Ho et al. (2007) indicate that these notions can be effective only in very specific situations, or are not effective at all. Article mentioned above is not an isolated work. Even in the case of High Frequency Trading systems one may observe that efficiency of automated trading systems decrease over time (Serbera et al., 2016). We propose to fill this gap by introducing a specially constructed system supporting the decision maker in the trading process. By a decision maker we understand a trader or any retail client with access to the Forex market. His/her goal is to achieve the highest possible profit from orders opened using signals generated from the set of trading rules. Nowadays, however, we can see a tendency for the number of potential instruments available to the decision maker on the Forex market to exceed a hundred. While the terms "decision maker" and "trader" in the present paper can be used simultaneously, we prefer to use decision analysis terms; therefore, in what follows we use the term "decision maker".

The approach introduced in this paper allows to initially estimate the set of currency pairs of potential interest for the decision maker. It should be clearly stated that our motivation is only to support the decision maker, and not to present an automatic trading system, so the main advantage of the proposed solution is that it assures the sovereignty of the decision maker (trader). The final decision whether to open a transaction for the given currency pair belongs to the decision maker. Thus, estimated set of variants can be regarded as a set of preliminary suggestions presented to the decision maker.

We propose an extension of the crisp approach currently used, where the signal is generated only in very specific market situations. In the crisp approach, the decision maker has a limited time to open the transaction when the signal has been generated. Thus the mechanism based on the binary values "signal / no signal" seems inefficient and for a large number of instruments often leads to the situation in which there is no single currency pair of potential interest to the decision maker.

In the fuzzy approach proposed here, there is a possibility to open a transaction in a predefined time interval related to the willingness of the decision maker to take the risk. This approach guarantees that the fuzzy approach is a generalization of the crisp approach, and the signals generated in the crisp approach are also included.

The outline of this paper is as follows. After the introduction, in Section 2, the notion of the crisp approach commonly used on the Forex market is briefly described. Next, the fuzzy approach along with the definitions of the membership functions are proposed. Section 3 includes a description of the proposed dominance-based algorithm generating non-dominated variants for the decision makers. Section 4 presents preliminary experiments conducted on real-world data. Finally, we present conclusions and suggest directions for future research.

2 Crisp and fuzzy systems

In the classical crisp approach, the rule-based trading system includes a predefined set of transaction rules involving technical indicators. Every indicator can be described by a set of rules which can be transformed into a binary activation function. A signal is generated only when the value of the function is equal to 1. In the fully automated-trading system a positive value of the function corresponds to opening the transaction, while in the crisp decision support system the information about the signal is derived in the system and presented to the decision maker.

We propose a fuzzy approach in which information about a market situation is transformed into a value of the membership function for each indicator. This value is calculated for every currency pair. Therefore, each currency pair in a given market situation at a time t is represented in the analysis as a variant with the vector of criteria related to particular indicators. To estimate the efficiency of this approach, we compare it with the classical crisp approach, where criteria for all indicators are constructed using the binary activation function. To accurately describe the proposed notion, we consider buy signals, but the same idea can be used for short sells.

To be more specific, we use two very popular technical indicators: the Relative Strength Index (RSI) and the Commodity Channel Index (CCI). The CCI indicator was originally proposed in the 1980s by Donald Lambert. The rules explaining the indicator are described in (www 1). A description of the RSI indicator can be found in Wilder (1978). These indicators are based on the so-called oversold and overbought levels and are frequently used to predict potential price changes. An example price chart with these indicators is shown in Figure 1. The overbought and oversold levels are in the upper and lower parts of the indicator windows. We have used the default parameters for the indicators with the overbought levels equal to 100 (for CCI), and 70 (for RSI). The oversold levels are equal to -100 and 30. In this particular example, the trading rule can be considered as the situation in which the indicator (CCI or RSI) crosses one of the levels defined above. If it crosses the oversold level upwards, the buy signal is generated. The sell signal is generated in the opposite case, when the overbought level is crossed downwards.

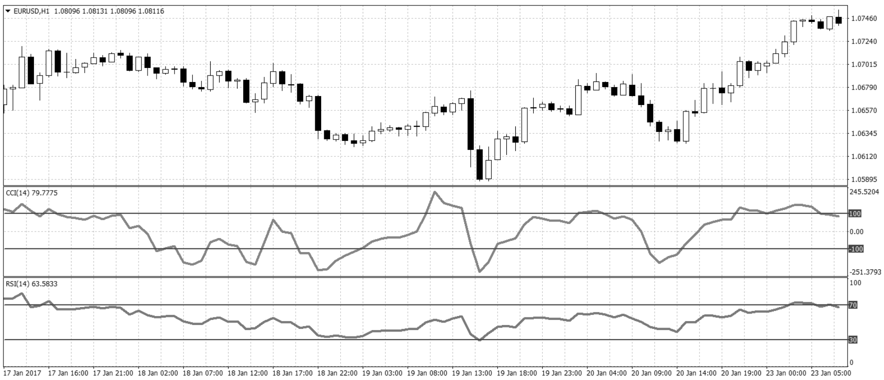

Figure 1. Example indicators and the price chart

The crisp signals for the RSI and CCI indicators are given by the formulas:

$$cond_{RSI} = true \text{ if } (RSI_n(t-1) < c_1) \wedge (RSI_n(t) > c_2), \tag{1}$$

$$cond_{CCI} = true \text{ if } (CCI_n(t-1) < c_1) \wedge (CCI_n(t) > c_2), \tag{2}$$

where $RSI_n(t-1)$ is the value of RSI at the time $t-1$ for the period n; $CCI_n(t-1)$ is the value of CCI at the time $t-1$ for the period n; c_1 and c_2 are constants related to their overbought and oversold levels.

We propose the fuzzy approach, in which the original signal taken from the crisp approach is still included. However, the adjacent values of the indicator can be also included by calculating the membership function:

$$\mu_{RSI}(c) = \begin{cases} \frac{RSI_n(t)}{30} \text{ if } (RSI_n(t) < 30), \\ 1 \text{ if } ((RSI_n(t-1) < 30) \wedge (RSI_n(t) > 30)) \\ \vee(RSI_n(t) = 31), \\ \frac{0.9}{RSI_n(t)-30} \cdot \alpha \text{ if } (RSI_n(t) > 31) \\ \wedge(RSI_n(t) < 50) \wedge (RSI_n(t-1) \leq 30), \\ 0 \text{ if } (RSI_n(t) > 50). \end{cases} \tag{3}$$

where α is a scalarizing factor in the range $\langle 0.5, 1.1\rangle$ and c is the currency pair for which the conditions on the right hand side of the equation are checked. The transaction system collects information from the market and calculates the values of the indicator at a given time t. Using the indicator the system checks the conditions and derives the value of membership function. The membership function for the CCI indicator is calculated as follows:

$$\mu_{CCI}(c) = \begin{cases} 0 \text{ if } (CCI_n(t) < CCI_{min}), \\ \frac{CCI_n(t)-CCI_{min}}{-CCI_{min}-100} \text{ if } (CCI_n(t) > CCI_{min}) \\ \wedge(CCI_n(t) < -100), \\ 1 \text{ if } (CCI_n(t-1) < -100) \wedge (CCI_n(t) > -100), \\ \frac{CCI_n(t)+50}{-50} \text{ if } (CCI_n(t) > -100) \wedge (CCI_n(t) < -50) \\ \wedge(CCI_n(t-1) > -100), \\ 0 \text{ if } (CCI_n(t) > -50). \end{cases} \tag{4}$$

where CCI_{min} is the minimal possible value of CCI and CCI_{max} is the maximal possible value of CCI. In the crisp case a signal can be observed only at a specific time tick – usually, when the indicator value is derived. In most cases the rules in the crisp approach use two adjacent values of the indicator. When the relation between these two values is satisfied (as in equation (1) or (2)), the signal for the decision maker is generated. In the fuzzy case the signal can be generated when the value of the membership function is higher than zero. Therefore the signal can be observed within a period longer than in the crisp approach and the decision maker has more time to make a decision.

3 A dominance-based algorithm

We will consider the buy signals. The sell signals can be treated in the same way. Let c be a currency pair valuated by a vector y of two criteria, $y = (y_1, y_2)$.

Variants of the vectors are analyzed in the criteria space $\mathbb{R}^2$. The criteria refer to the RSI and CCI indicators with the values of membership functions: $y_1 = \mu_{RSI}(c)$ and $y_2 = \mu_{CCI}(c)$ for a given currency pair c. The transaction system generates several such variants in a given time window. By a time window we understand a time needed to generate a new value on the price chart.

The decision maker, i.e. trader, tries to find a variant with the maximal values possible of all the criteria; therefore the following relations between variants are considered in $\mathbb{R}^2$ space:

Definition 3.1 *A variant y is at least as preferred as a variant z if each criterion of y is not worse than the respective criterion of z:*

$$y \succeq z \Leftrightarrow (y_1 \geq z_1) \wedge (y_2 \geq z_2). \tag{5}$$

Definition 3.2 *A variant y is more preferred (better) than a variant z if the following holds:*

$$y \succ z \Leftrightarrow (y \succeq z) \wedge \neg(z \succeq y). \tag{6}$$

Definition 3.3 *A variant y is incomparable with a variant z if:*

$$\neg(y \succeq z) \wedge \neg(z \succeq y). \tag{7}$$

The domination relation 6 defines a partial order in the space of criteria. We propose algorithm 1 for deriving non-dominated variants to be analyzed by the decision maker. The following notation is used in the algorithm.

- Y is the set of all variants considered in a given time window.
- $u = (1, 1)$ is assumed to be the aspiration point of the decision maker. If there exists a variant equal to the aspiration point, it should be considered as the only rational choice for the decision maker.
- x is the reservation point assumed by the decision maker. All variants dominated by this point are removed from further analysis. The reservation point x relates to the willingness of the decision maker to take a risk by extending the set of accepted variants as compared with the crisp approach. To be more specific, greater risk leads to the possibility of accepting potentially worse variants instead of delivering an empty set of variants to the decision maker.
- ND denotes the set of all non-dominated variants of potential interest to for the decision maker in a given time window.

- Y_- is the set of points removed from the analysis in the algorithm, initially the points dominated by x, i.e. $Y_- = (x + \mathbb{R}^2_- \setminus \{0\})$, where $\mathbb{R}^2_-$ is the negative cone. Moreover, it is the set of all points dominated by x and by the variants currently included in ND.

- Y_+ denotes the set of points accepted for further analysis in the algorithm, $Y_+ = Y \setminus Y_-$.

The algorithm, called the Dominance-based algorithm, allows for the generation of all non-dominated variants in the initial set Y_+ accepted for analysis on the basis of the reservation point x defined by the decision maker.

The steps of the algorithm can be divided into three phases. In the first phase the set Y is derived by calculating the criteria: membership functions for currency pairs in the assumed time window. At the same time, the sets Y_- and Y_+ are derived using reservation point x (lines 1–3). In the second phase (lines 4–5) variants equal to the aspiration point are looked for. If such a variant/variants exists, the algorithm is halted and the resulting set ND includes only these variants to be selected by the decision maker as his obvious rational choice. The third, and the most complex phase of the algorithm consists of lines 6–18. Three situations can occur: first if a selected variant y is included in Y_-, then it is removed from the analysis; second: if ND is empty, then the variant y is added to ND. The third situation occurs when ND is not empty. In this case variant y is compared with every variant from ND. The variants from ND dominated by y are removed from ND and y is added to ND. If the variant y is dominated by any variant of ND, the variant y is removed from the analysis. After each of these three situations Y_- is updated so that the area which it covers is expanded by the negative cone moved to y.

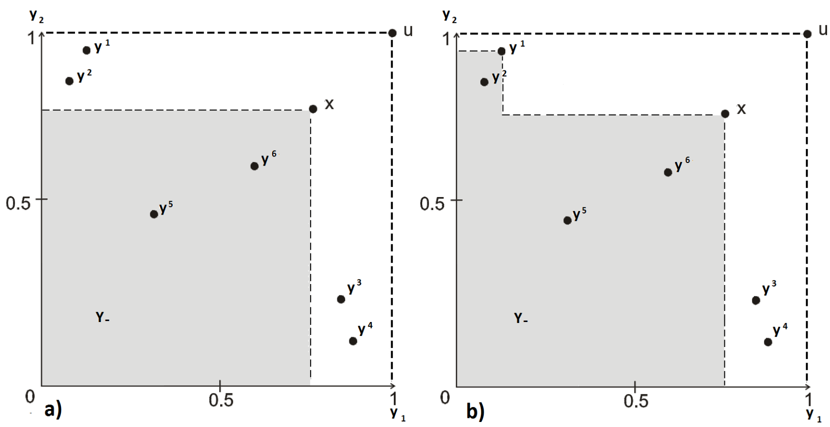

Figure 2. An ilustrative example

Algorithm 1: Dominance-based algorithm

begin
  Fix the aspiration point u, create the sets Y and $ND = \emptyset$
  The decision maker sets the point x defining the nonaccepted variants
  Generate sets Y_- and Y_+
  if *there exists* $y \in Y$ *such that* $y = u$ **then**
    $ND = \{y\}$ End of the algorithm
  for *each variant* y *in* Y_+ **do**
    if $y \in Y_-$ **then**
      Delete y from further analysis, i.e. $Y_+ = Y_+ \setminus \{y\}$
    else if $y \notin Y_- \wedge ND = \emptyset$ **then**
      Add y to ND and Update Y_- and $Y_+ = Y_+ \setminus \{y\}$.
    else
      for $z \in ND$ **do**
        if $y \succ z$ **then**
          Delete z from ND
        else if $z \succ y$ **then**
          Mark y as dominated, delete it from Y_+, and BREAK
      if *y is non-dominated* **then**
        Add y to ND
        Update $Y_- = Y_- \cup (y + \mathbb{R}^2_- \setminus \{0\})$
        Delete y from further analysis, i.e. $Y_+ = Y_+ \setminus \{y\}$
  if $Y_+ = \emptyset$ **then**
    end the algorithm

An illustrative example is presented in Figure 2. In part a) an initial simple situation is shown with a given reservation point x and a set Y consisting of six variants. Variants y^5 and y^6 are removed from further analysis because they are dominated by the reservation point x, as they belong to the initial set Y_- (marked in grey). An analysis of four remaining variants (y^1, y^2, y^3 and y^4) is illustrated in Figure 2b). At the beginning, ND is empty, and y^1 is outside the grey area, thus it is added to ND. The set Y_- is extended as follows:

$$Y_- = Y_- \cup (y^1 + \mathbb{R}^n_- \setminus \{0\}). \tag{8}$$

After the update of Y_-, variant y^2 is an element of Y_-, thus it is excluded from further analysis. Variants y^3 and y^4 are mutually incomparable and incomparable with y^1 (y^1 is already in ND). In this particular scenario both variants are added to ND. The grey area representing Y_- is expanded again. There are no more variants left, thus the algorithm halts. All non-dominated variants $\{y^1, y^3, y^4\}$ are in ND and can be presented to the decision maker.

4 Preliminary experiments

For the tests with real data we have selected 68 variants (currency pairs) from January 2017. We tested three time windows: 5 minutes (high frequency trading), 1 hour (intraday trading), 1 day (long-term trading). For every time window we have assumed three different positions of the reservation point in the criteria space: $x = (0.25, 0.25)$, $x = (0.5, 0.5)$ and $x = (0.75, 0.75)$. For every combination of these parameters (time window and reservation point position) we included 15 successive readings. The overall time of the experiments was equal to the length of the single time window multiplied by the number of readings. By a reading we understand a single situation on the price chart which is generated in the specific time window. To simplify: every new situation on the price chart corresponds to a new reading. The computation time for a single reading (including the generation of the non-dominated set ND) was approximately 2 seconds.

First of all, we derived variants which were not dominated by the reservation point. The numbers of such variants are presented in Table 1. They allow to estimate the potential number of variants (included in Y_+) which must be analyzed in detail. The table presents the cardinality of Y_+ for different time windows and different positions of the reservation point x. Lower values of the coordinates of the reservation point x indicate a higher willingness of the decision maker to take the risk. At the same time the cardinality of Y_+ is increased.

Table 1: The number of variants analyzed by the system with two indicators (RSI and CCI)

	M5			**H1**			**D1**		
x=	**0.25**	**0.5**	**0.75**	**0.25**	**0.5**	**0.75**	**0.25**	**0.5**	**0.75**
Reading 1	15	14	9	15	8	6	18	13	9
Reading 2	15	14	11	16	14	6	14	8	7
Reading 3	22	16	12	22	19	13	20	13	11
Reading 4	25	23	19	29	25	19	19	17	12
Reading 5	33	28	23	27	24	23	23	19	11
Reading 6	26	19	16	12	11	9	30	22	16
Reading 7	21	18	14	18	13	6	29	26	19
Reading 8	20	11	10	24	20	17	37	31	20
Reading 9	17	14	7	21	16	10	33	28	27
Reading 10	22	15	12	21	13	8	25	22	17
Reading 11	15	10	3	25	20	17	23	20	17
Reading 12	11	11	9	27	21	19	20	16	13
Reading 13	19	15	10	19	15	12	25	18	11
Reading 14	22	20	15	21	16	11	33	22	22
Reading 15	17	13	9	27	22	18	20	15	15

After the preliminary selection of the variants included in the analysis, all the non-dominated variants were derived at the end of the given time window. The whole procedure was repeated for 15 successive readings. The results – the cardinality of the set ND for the time window of 5 minutes are presented in Table 2. The number of non-dominated variants derived for different positions of the reservation point decreases when the position of the point is moved in the direction of the aspiration point u. In the crisp approach the results are presented in the last column of Table 2. It should be noted that the rows with the same numbers for each column (Readings 2, 4 and 10) indicate the cases when variants equal to the aspiration point were found. These variants are presented to the decision maker as the only rational choices. Especially interesting are the cases in which the number of variants available for the decision makers is small. They can be observed in Readings 11 and 15, where in the first case the crisp approach generated no variant at all, while the fuzzy approach generated two variants for each value of x. In the second case, the crisp approach generated only one variant, while the number of variants derived from the fuzzy approach was: two for $x = 0.75$ and three for $x = 0.5$ and $x = 0.25$. In general, the set of solutions generated for the crisp case contains only the variants which were found in the corners of the criteria space, where the membership function for one of the indicators is equal to 1. The fuzzy approach generates all non-dominated variants generated in the crisp case. It also allows to extend the set of acceptable variants by the non-dominated variants for which a deviation from the aspiration point u is limited by the reservation point x. Namely, the non-dominated variants belong to the set $(u + \mathbb{R}^n_-) \setminus (x + \mathbb{R}^n_- \setminus \{0\})$.

Table 2: The number of non-dominated variants generated in the fuzzy case as compared with the number of variants generated in the crisp approach – – 5 minutes time window

	M5			
x =	**0.25**	**0.5**	**0.75**	**Crisp**
Reading 1	7	7	5	2
Reading 2	1	1	1	1
Reading 3	12	9	9	5
Reading 4	3	3	3	3
Reading 5	18	16	14	9
Reading 6	9	8	7	3
Reading 7	8	8	8	6
Reading 8	8	7	5	3
Reading 9	5	5	3	2
Reading 10	1	1	1	1
Reading 11	2	2	2	0
Reading 12	7	7	7	4
Reading 13	10	8	7	5
Reading 14	10	9	8	5
Reading 15	3	3	2	1

In Table 3 we present similar results for the cardinality of ND for the time window of 1 hour. Once again, the comparative results for the crisp approach are given in the last column. In Readings 2, 7 and 14 once again the number of variants derived in the crisp approach was very small, while the application of the fuzzy method increased the number of non-dominated variants derived for the decision maker. A shortcoming of the system can be observed in the readings 5, 12 and 13, where the advantage of the fuzzy approach is not visible due to a large number of variants derived for the decision maker from the crisp approach. In such situations an analysis based on a greater number of indicators should be made. If the fuzzy approach generates a large number of non-dominated variants, an appropriate ranking method should be applied.

Finally, the results for the longest time window considered on the Forex market as the long-term trading (1 day time window) which covered approximately three weeks from January 2017 are presented in Table 4. Once again, the most useful information for the decision maker is generated for Reading 2, where the crisp approach resulted in one variant only, while in the fuzzy case at least three variants have been generated.

Table 3: The number of non-dominated variants generated in the fuzzy case approach as compared to the number of variants generated in the crisp approach – 1 hour time window

	H1			
x =	**0.25**	**0.5**	**0.75**	**Crisp**
Reading 1	6	5	5	3
Reading 2	3	3	2	1
Reading 3	6	6	5	3
Reading 4	2	2	2	2
Reading 5	20	20	19	17
Reading 6	8	7	6	4
Reading 7	5	5	4	2
Reading 8	14	10	10	7
Reading 9	9	7	6	4
Reading 10	5	5	5	2
Reading 11	9	8	7	4
Reading 12	16	14	12	10
Reading 13	15	13	11	10
Reading 14	7	7	5	3
Reading 15	1	1	1	1

Table 4: The number of non-dominated variants generated in the fuzzy case approach as compared to the number of variants generated in the crisp approach – 1 day time window

	D1			
x =	**0.25**	**0.5**	**0.75**	**Crisp**
Reading 1	2	2	2	2
Reading 2	4	3	3	1
Reading 3	10	8	7	5
Reading 4	9	9	7	5
Reading 5	7	7	5	3
Reading 6	9	8	4	2
Reading 7	13	12	12	5
Reading 8	9	8	8	4
Reading 9	6	6	6	6
Reading 10	10	10	9	6
Reading 11	1	1	1	1
Reading 12	11	10	10	5
Reading 13	2	2	2	2
Reading 14	9	9	8	3
Reading 15	11	10	10	7

5 Conclusions

In this paper we have presented an extension of the classical crisp approach used in rule-based trading systems on the Forex market. The suggested approach provides an opportunity to extend the set of variants of possible interest for the decision maker. The fuzzy notion is presented as a generalization of the notions commonly used in rule-based trading systems. Along with the implementation of fuzzy membership functions, an algorithm generating the set of non-dominated solutions has been presented. The algorithm is especially useful when the traditional crisp approach generates no signals at all, but the fuzzy approach provides variants with the membership function close to 1. The notion of a reservation point is related to the risk aversion of the decision maker.

The proposed approach assures the full sovereignty of the decision maker. He decides how far he wants to extend the set of variants analyzed by the system in comparison to the crisp approach. He obtains the generated non-dominated variants. The decision maker decides which variant he will use to make a position.

The proposed approach is flexible. It can be used with various time windows and even with a different set of instruments. The position of the reservation point in the criteria space can be changed for every new reading. The approach, presented here for two indicators, can be easily extended to handle a greater number of them. A greater number of indicators included in the system should significantly reduce the set of non-dominated variants. Especially interesting can be such indicators as the moving average (Holt, 2009), money flow index, Ichimoku and others (Patel, 2010).

At the preliminary stage of our experiments we assumed that there are no complex dependencies between the two indicators. However, in general this is not strictly true for a greater number of different indicators. There are indicators which should be analyzed jointly under additional assumptions. Complex dependencies and complex transaction systems will be introduced in the proposed method. Finally, generating a large and difficult set of non-dominated variants naturally forces a ranking of the variants which could greatly improve the final analysis performed by the decision maker. An appropriate ranking method will be included in the system. Different ranking approaches are discussed, including ideas based on the notion of a concession line (Juszczuk et al., 2016), the dominance-based rough set approach (Greco et al., 2002), or the bipolar method (Konarzewska-Gubała, 1989).

As mentioned before, the presented approach provides an initial simple version of the system, which can be expanded in many ways. Among the increasing number of papers dealing with more complex systems based on the technical analysis indicators, two distinct extensions seem especially interesting. Both are related to social phenomena, which could be used in the systems. The first extension assumes the introduction of a fundamental analysis translated into easily understandable numeric values of the fundamental indicators. The second one is strictly related to social trading regarded as a mechanism for collaborative trading on the market. The effectiveness of social trading and systems based on social networks (such as twitter) is particularly difficult to estimate. On the other hand, it is possible to estimate the activity of traders using such notions as gamification. These concepts will therefore be discussed in future papers.

References

Barbosa R.P., Belo O. (2008), *Autonomous Forex Trading Agents*, Advances in Data Mining. Medical Applications, E-Commerce, Marketing, and Theoretical Aspects, Lecture Notes in Computer Science, 5077, Springer.

Cheol-Ho P., Irwin S.H. (2007), *What Do We Know about the Profitability of Technical Analysis?* Journal of Economic Surveys, 21(4), 786-826.

Greco S., Matarazzo B., Słowiński R. (2002), *Multicriteria Classification by Dominance-based Rough Set Approach*, Handbook of Data Mining and Knowledge Discovery, Oxford University Press, New York.

Hirabayashi A., Aranha C., Iba H. (2009), *Optimization of the Trading Rule in Foreign Exchange Using Genetic Algorithm*, Proceedings of the 11th Annual conference on Genetic and evolutionary computation GECCO '09, 1529-1536.

Holt C.C. (2004), *Forecasting Seasonals and Trends by Exponentially Weighted Moving Averages*, International Journal of Forecasting, 20(1), 5-10.

Juszczuk P., Kaliszewski I., Podkopaev D., Hsu-Shih S. (2016), *Market Collective Wisdom Discovery for Portfolio Investments*, International Journal of Information and Management Sciences, 27, 87-102.

Kablan A. (2009), *Adaptive Neuro Fuzzy Inference Systems for High Frequency Financial Trading and Forecasting*, Advanced Engineering Computing and Applications in Sciences, ADVCOMP '09.

Konarzewska-Gubała E. (1989), *BIPOLAR: Multiple Criteria Decision Aid Using Bipolar Reference System, LAMSADE*, Cashier et Documents, 56, Paris.

Lai K.K., Yu L., Wang S. (2005), *A Neural Network and Web-Based Decision Support System for Forex Forecasting and Trading*, Data Mining and Knowledge Management, Lecture Notes in Computer Science, 3327, Springer.

Liu Z., Xiao D. (2009), *An Automated Trading System with Multi-indicator Fusion Based on D-S Evidence Theory in Forex Market*, Fuzzy Systems and Knowledge Discovery, FSKD'09.

McLeod G. (2014), *Forex Market Size: A Traders Advantage*, dailyFx, January 24, https://www.dailyfx.com/forex/education/trading (access: 25.04.2017).

Nassirtoussi A.K., Aghabozorgi S., Wah T.Y., Ling Ngo D.C. (2015), *Text Mining of News-headlines for FOREX Market Prediction: A Multi-layer Dimension Reduction Algorithm with Semantics and Sentiment*, Expert Systems with Applications, 42(1), 306-324.

Patel M. (2010), *Trading with Ichimoku Clouds: The Essential Guide to Ichimoku Kinko Hyo Technical Analysis*, Wiley & Sons.

Serbera J.P., Paumard P. (2016), *The Fall of High-frequency Trading: A Survey of Competition and Profits*, Research in International Business and Finance, 36, 271-287.

Slany K. (2009), *Towards the Automatic Evolutionary Prediction of the FOREX Market Behaviour*, Adaptive and Intelligent Systems, ICAIS '09.

Wilder W. (1978), *New Concepts in Technical Trading Systems*, Trend Research.

Yao J., Tan Ch.L. (2000), *A Case Study on Using Neural Networks to Perform Technical Forecasting of Forex*, Neurocomputing, 34(1-4), 79-98.

Yu L., Lai K.K., Wang S. (2005), *Designing a Hybrid AI System as a Forex Trading Decision Support Tool*, Tools with Artificial Intelligence, ICTAI '05.

(www 1) Investopedia, http://www.investopedia.com/articles/trading/05/041805.asp (access: 10.04.2017).