PROPERTY ANALYSIS OF ALGORITHMIC TRADING SYSTEMS BASED ON BINARY REPRESENTATION

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***Abstract**: In the article we present methods of appointing parameters for performance evaluation of algorithmic trading systems constructed based on state models in a binary representation. In the presented considerations, risk analysis and parameters significant for the investment practice of CFD contracts are included. Further in the article we propose a detailed schema of appointing parameters for an algorithmic trade system that include such factors as risk aversion, capital held, or subjective preferences of the investor. Researched methods allow for implementing in practice the analyzed algorithmic trade systems along with the risk assessment and the expected return rate. Results of the considerations are illustrated with an exemplary algorithmic trading system analysis, with the system being built based in binary state model (BMS). In the performed research we used original software written in C++ and Mql4 languages and historical tick data for XAU/USD from a six-year time period (2012-2019).*

Key words: *High Frequency Econometric, Technical Analysis, Investment decision support, Risk analysis*
JEL codes: *F31, G11, G14, C49*

1. Introduction

Methods of technical analysis and exchange rate modeling are created in order to suport investors in decision-making (e.g. indicators) or in order to fully automatize the investment process in form of algorithmic systems (e.g. HFT systems). The vast majority of research propose different models and methods of prediction, without analyzing the possibility of practical implementation, taking into account the market reality (e.g. provision, risk analysis, etc.).

In the article we present methods of assessment and selection of trade parameters (position size) for investment strategies, constructed based on state models in a binary representation, including investor's subjective criteria, pertaining for example risk aversion, expected return rate, etc.

This paper is organized in the following way. After the introduction, in the second chapter we present the concept of binary representation. The third chapter we present ideas and results of state modelling. The fourth chapter shows the concept of building a HFT system. Next chapter introduces the criteria of evaluating strategies, selection of risk analysis methods and a schema for selecting parameters depending on the investor's preferences. In this chapter we also present an empirical example of a strategy analysis and trade parameters selection using criteria given by the investor for XAU/USD exchange rate.

2. Binary representation

The exchange rate trajectory changes with each tick, that is every 1-2 seconds. Because of the huge variability of changes using tick charts in technical analysis methods is rather impossible. Because of this fact, in order to analyze and model the exchange rate, generally the candlestick representations are used (Burgess, 2010; Kirkpatrick and Dahlquist, 2010). The candlestick representation dominates in technical analysis methods (visual analysis). Candle parameters are used in order to calculate the most popular indicators e.g. RSI, MACD (Vezeris et al. 2018), etc. (Kirkpatrick and Dahlquist 2010)). Candlestick representation is also usually used in scientific research and investment practice. It is applied by all broker platforms, e.g. MetaTrader, JForex (Gallo 2014).

Using candlestick representation leads to a loss of an indefinite and time variable informative value, pertaining the order and scope of exchange rate trajectory changes "inside" the candle. This information loss is highly significant in case of creating HFT systems, since the lack of a proper information in modeling can lead to results that are far from expectations, for systems created based on historical candlestick data.

Using tick data in order to analyze exchange rate trajectory is also not a good solution since the data is noisy (Lo et al. 2000), and the analysis of thousands of changes of a 1-2 pips range can prevent correct modeling.

In order to eliminate the noise and to include all significant changes (from the point of view of the analysis), in (Stasiak 2016) the Author proposed a so-called binary representation.

The binary representation was inspired by a visual point-symbolic method (De Villes 1933). It presents the course trajectory changes in form of a binary sequence $\{\varepsilon_i\}_{i=1}^{n}$, where *n* is the number of changes. Each exchange rate course change of a given value (called 'discretization value' (δ)) is assigned a proper binary value. If the course falls below the lower limit, the algorithm assigns the i-th change the binary value ε_i=0, and if it rises above the upper limit, the binary value of ε_i=1. In the next steps, the algorithm calculates next upper and lower limits, regarding the current course value. The binary representation (Stasiak 2016) can be expanded by additional information, e.g. change duration (Stasiak 2018a) or information about the wave character of the course trajectory (Stasiak 2017). The binary representation allows for an effective course modelling, creating prediction models and, in consequence, constructing algorithmic trade systems.

3. State modeling

Exchange rate trajectory changes for financial instruments are a result of a simultaneous impact of many factors. Among them we can distinguish macroeconomic parameters, geopolitical situation and others (Cheung and Chinn 1999). The course trajectory is also influenced by the investors' behaviour with its psychological background. Taking into account all of the factors influencing the present value of a course is practically impossible, therefore the exchange rate modelling should consist in the unambiguous identification of investor behavior patterns and indication of the most common statistical responses to such patterns.

State modelling of the exchange rate trajectory in a binary representation consist of identification of behavioural patterns of the investors as binary representation subsequences of given parameters (Stasiak 2018b). Next, based on statistical analysis of historical data, we calculate probability distributions for the future change directions, which are a reaction to a given behaviour of the investors. Up till today some state models were already researched, such as Binary State Model (BSM) (Stasiak 2016), Binary-Temporal State Model (BTSM) (Stasiak 2018) and Wave-Binary State Model (WBSM) (Stasiak 2017). The distributions obtained during the modelling can be put in a so-called prediction table. An example of this kind of a table for a BSM was presented in Table 1. States s_j in Table 1 correspond to the given bahaviour patterns and are represented by binary subsequences (Stasiak 2016).

Table 1. Prediction table

State s_j	Probability of the exchange rate dropping by δ	Probability of the exchange rate increase by δ
s_1	0,469	0,531
s_2	0,425	0,575
s_3	0,595	0,405
s_4	0,527	0,473

The prediction tables are the base for algorithmic trade and are constructed based on the state models in a binary representation. A detailed description of the particular models performance can be found in (Stasiak 2016, 2017, 2018a).

4. The concept of HFT system construction

The idea of constructing HFT systems dedicated to the binary representation consist of matching each change in the binary representation (that is a fall or a rise of the course trajectory by the value of the appointed discretization value (δ)) with a single transaction. As a consequence, each course change in the binary representation is a potential transaction. The transactions are made according to the probability distribution of the future course trajectory change obtained from the state modelling, for chosen states of the analyzed market.

In the prediction table, the probability values can differ for different states. Therefore, limiting the scope of possible investment decisions to a given number of states (so called decision state space) can be beneficial for the investor. As a consequence, all transactions will be opened only if the states from the decision state space occur. If the indicated state occurs, the investor obtains a revenue y_i from the given transactions, which equals:

$$y_i = l * (\delta - \overline{spr}). \tag{1}$$

On the other hand, in case of a wrong recommendation:

$$y_i = -l * (\delta + \overline{spr}), \tag{2}$$

where l is the size of a single position, and $\overline{spr}$ is the constant spread. We assume that the position size is constant for all transactions. The final balance ($S(t_k)$) is a sum of revenues and loses from realized transactions and the initial balance ($S(t_0)$) :

$$S(t_k) = S(t_o) + \sum_{j}^{j<N} y_j, \tag{3}$$

where N is the number of transactions made.

The best form of performance evaluation for the system is making a backtest. Based on it it is possible to analyze the characteristics and investment risk. In order to unambiguously identify the system and the periods for which the backtest prediction table was appointed, we introduce the following notation:

Name_bc({representation_parameters};{system_parameters};$\{P\_dec\}$;$\{l_{bt}, \overline{spr}, S(t_0)_{bt}\}$;
$\{\, t^{tab\_p}_{Start}, t^{tab\_p}_{Stop}, t^{bc}_{Start}, t^{bc}_{Stop}\}$)

where $t_{Start}^{tab\_p}$ and $t_{Stop}^{tab\_p}$ are the dates of the start and the end of the period, for which the prediction table was appointed, and t_{Start}^{bc} and t_{Stop}^{bc} are dates of the start and the end of the period, for which the backtest was made. P_dec is the set of decision states. Representation_parameters and Sysem_parameters are parameters dependent on the appointed representation and model. They influence, for example, the prediction table.

The initial balance and the position size do not influence the change character. The position size *l* only scales the backtest results. Figure 1 presents an example of a backtest of a system, for different position sizes. However, the selection of position size, depending on the initial balance, influences the undertaken risk and can be calculated based on system characteristics analysis and investor's capital.

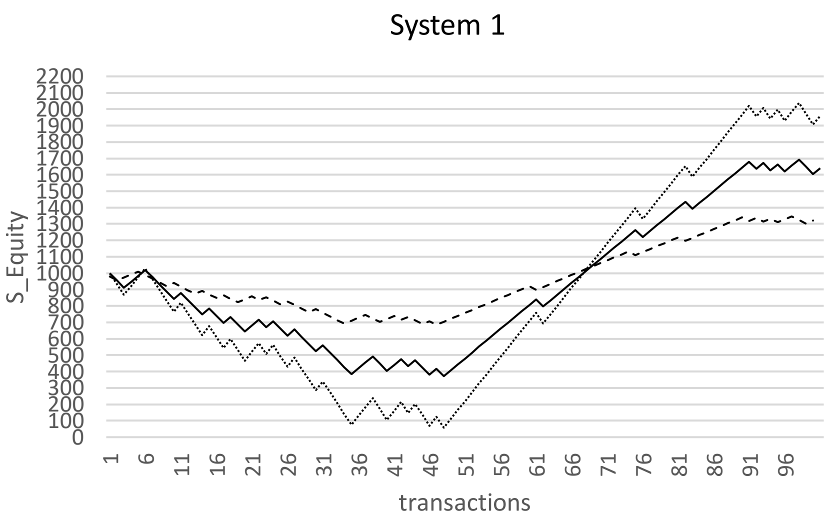

Figure 1. Backtest results of an exemplary system for 1, 2 and 3 lots.

5. HFT system properties

5.1. Risk analysis – tool selection

The main goal of each investor is to maximize the revenue and to minimize the risk. Risk calculation depends on the type of financial instrument in consideration. As an example, for the stock market, a short-term, few-hours-long fall of a stock value, resulting from e.g. a gossip, can surely be omitted, since it does not influence the bankruptcy risk of the investor. On the other hand, in case of CFD contracts, such kind of fall can result in losing all capital. In the descriptions of the systems created for CFD contracts it is commonly assumed, that the risk measure is in the form of the maximal capital loss (mdd) (de Melo i Brandi 2004, Pardo 2011, Pospisil i Vecer 2008):

$$mdd = \max_{t \in (0,T)} \left\{ \max_{s \in (0,t)} S(s) - S(t) \right\}, \tag{4}$$

where $S(t)$ is the investor's balance at the time t, and T denotes the performance time of the algorithmic trade system.

Using statistical methods for systems using CFD contracts is not effective because of two reasons. Firs one is that the distribution of the return rates is not consistent with the normal distribution. The second reason is that the *mdd* parameter is influenced by the order and not by the statistical dominance of the number of profitable transactions over lossy ones.

Figure 2 depicts two examples of a backtest of a HFT system (that is an algorithmic trade system characterized by a vast number of changes). In both cases, statistically 60% of transactions ended with a revenue, and the risk measured by *mdd* parameter is significantly different (*mdd_1*=620$, *mdd_2*=160$). This example shows that the probability given in the prediction table can be used in order to make recommendations, yet it cannot stand as a base to calculate the risk. In accordance with (Aldrige 2010, de Melo and Brandi 2004, Pardo 2011, Pospisil and Vecer 2008) we therefore appoint maximal capital loss as the risk measure.

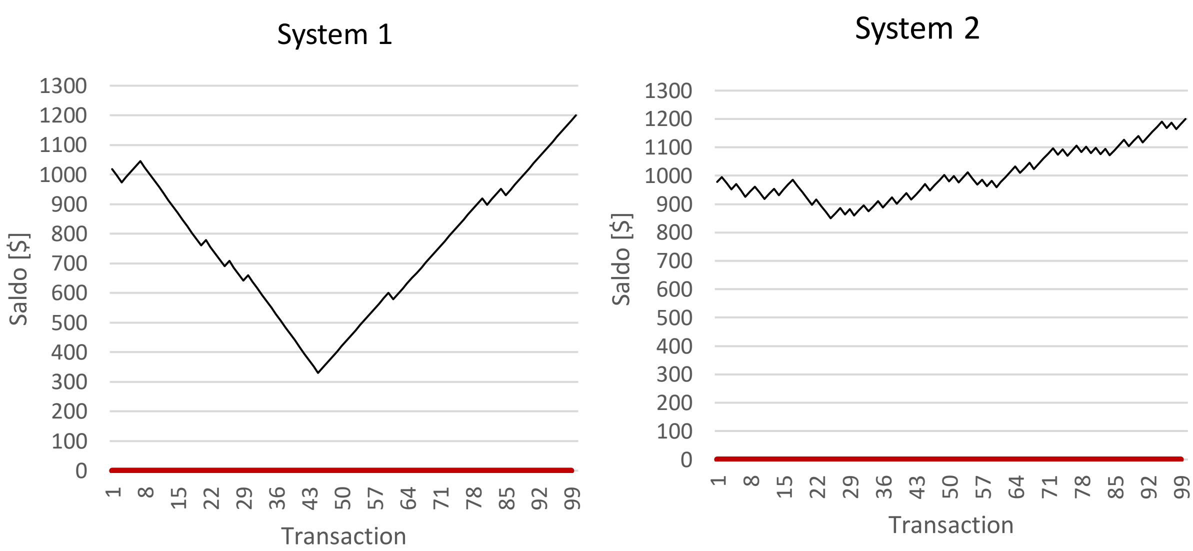

Figure 2. Backtest results for System 1 (2a) and System 2 (2b)

5.2. System characteristics assessment

Each investor strives to maximize their revenue and minimize undertaken risk. In order to evaluate the HFT systems with this outlook in mind, appropriate financial effectiveness indicators are used. System characterized by the highest effectiveness can assure the highest return rate with the same risk level. There exist three basic effectiveness coefficients which use *mdd* as the risk measure: Calmar's, Sterling's and Burke's (Aldrige 2010). In order to assess effectiveness in the context of CFD-dedicated systems, the Calmar's indicator was chosen. The indicator uses *mdd* in the explicit form. It can be calculated with use of the following formula:

$$\mathrm{Calmar_i} = \frac{-E_{bc}^{r}}{mdd_{bc}}, \quad (5)$$

where $\mathrm{E_{bc}^r}$ is the average annual return rate and $\mathrm{mdd_{bc}}$ is a maximal capital loss obtained during a backtest. A prerequisite for achieving a positive rate of return is an index value greater than one.

Two additional parameters were introduced to the system assessment: the minimum transaction frequency (MCT) and the maximum duration of the fall (MCS). The MCT parameter specifies the minimal number of transactions made in the adopted unit of time (year) during the backtest. The MCS parameter allows to specify the maximal time between occurrences of subsequent increases in the balance. The investor can subjectively define the conditions that MCT and MCS parameters must meet to make the system acceptable.

5.3. Selection of system parameters for individual investor preferences

If the Calmar coefficient is positive and the minimum values set by the investor in the backtest are met, the investor may start investing. However, for this purpose the size of the position (*l*) should be calculated first. The selection of the position size can be made based on the strategy properties obtained from a backtest (that was carried out for any balance and size of the position), the initial balance and individual preferences of the investor (e.g. regarding risk aversion).

It was assumed that the measure of risk is the maximum level of capital decline. Therefore, knowing the historical value of the parameter mdd_{bt}, calculated based on the performed backtest, the size of position *l* can be appointed, so that when such a fall occurs again, the loss will be a percentage of the capital, determined by the investor. Because the distribution of changes in the investor's balance is not known, it is also not possible to assess whether in the future there may be a larger maximum decrease in capital than the one registered in the backtest. In response to this uncertainty, the investor, depending on his risk aversion, sets the level of security, that is the so-called safety factor (*sf*) (Pardo 2011). This parameter can be interpreted as a reserve of funds to cover any falls lower then maximal loss registered in the backtest.

The level of security therefore determines how much the investor's initial balance is greater than the absolute value of the largest historical capital loss. Assuming the above, the relationship between the investor's initial capital, size of the position, safety level *sf* and the maximal capital loss obtained in the backtest for the given position size can be derived as follows:

$$S(t_0) = sf * l * \frac{mdd_{bt}}{l_{bt}}, \tag{6}$$

After elementary transformations we obtain a relation that can be used to describe the size of position in which the transactions should be made in order to ensure the given level of risk:

$$l = \frac{S(t_0) * l_{bt}}{mdd_{bt} * sf}. \tag{7}$$

Because the return rate depends directly on the position size (*l*), therefore the expected annual return rate (E_o^r) can be calculated based on the following dependency:

$$E_o^r = E_{bt}^r \frac{l_{bt}}{l}. \tag{8}$$

where $\mathrm{E}_{\mathrm{bt}}^{\mathrm{r}}$ i san average annual return rate obtained in the backtest.

5.4. Analysis and parameter selection for an exemplary algorithmic trading system

Let us consider an investor with a balance equal to $S(t_0)$ =10 000$. By analyzing the risk, the investor determined an acceptable safety level as 3 (occurrence of mdd_{bt} 3 times greater than the one registered in the backset will result in bankruptcy). They also expect a minimum of 1 transaction per day (MCT = 250) and accepts a minimum duration of the fall of 9 months (MCS = 273). They will only invest if the expected average annual rate of return exceeds 10%. The investor received a proposal to invest in the "System_1" system, constructed based on the BSM model. In order to make a decision, the investor analyzes a 4-year backtest (presented in Figure 3).

Based on the backtest analysis we can conclude that the system is characterized by the following parameters:

- *Cal*=1.31869
- *MSC*=1092
- *MCT*=260.43

Investor's requirements pertaining the MSC and MCT parameters are thus met, and the positive financial effectiveness indicates a positive return rate. The precise value of the expected return rate depends on the position size *l*, and this one in turn depends on the capital and risk aversion. For the set safety level and using formula (7) we can assess the position size for the given capital, which equals l = 0.39 Lot. Next, based on the position size, we can calculate the expected annual rate of return (formula 8), which equals E_o^r = 11.12%.

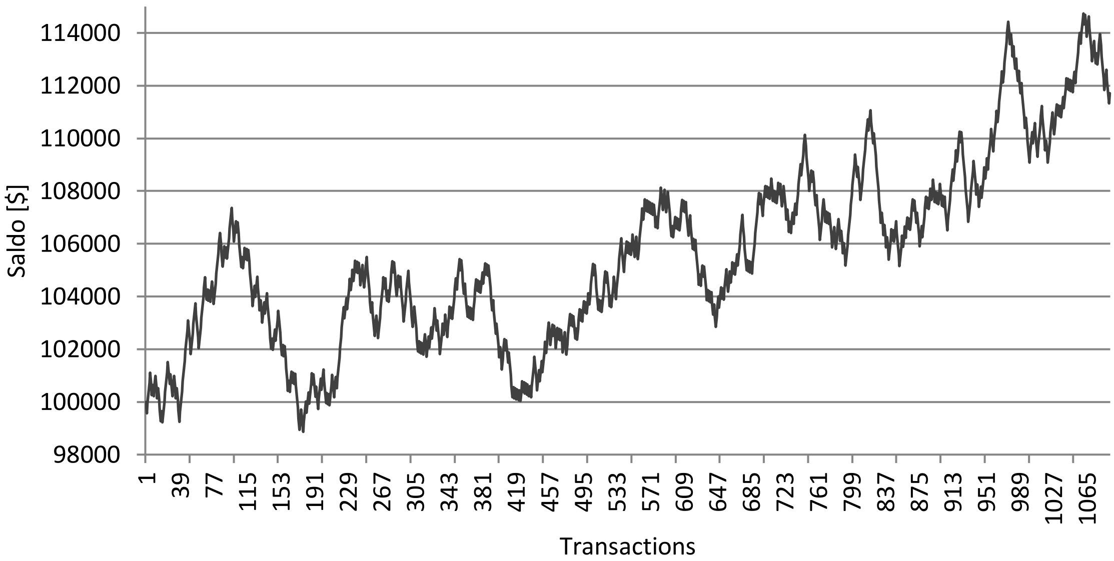

Figure 3. Backtest results for System 1 ({XAU/USD, *DU*=404 pips};{m=3}; {l_{bc} =1Lot, $\overline{\mathrm{spr}} = 20$ pips, $S(t_0)_{bc}=100\,000\$$}; {01.01.2013, 31.12.2014, 01.01.2015, 01.01.2019})

Performed analysis of the System 1 confirmed the investor's expectations and justifies using the system in investment practice.

6. Summary

In the article we presented methods for analyzing properties and selecting parameters for algorithmic trade systems, constructed based on state models in binary representation. Proposed methods take into account both investment practice and subjective preferences of an investor, such as risk aversion.

The article shows an example of using the BSM in order to construct a HFT system for XAU/USD CFD contracts. A risk analysis was performed, with use of a backtest and proposed methods. It was verified, whether the system meets the investor's requirements and both the size of the position and expected return rate were calculated for the safety level set by the investor.

The example presented in the article additionally confirms the sensibility of usinf the state modelling in a binary representation in order to create algorithmic trade systems characterized by a positive return rate in market reality.

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