Journal of Theoretical and Applied Information Technology
15th November 2023. Vol.101. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A MULTI-EXPERT APPROACH TO IMPROVING DICTIONARY-BASED SENTIMENT ANALYSIS WITH CORRELATED FOREX MARKET DATA

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ABSTRACT

One challenge in automatically extracting knowledge from text documents is processing messages where the content is presented implicitly or in a veiled manner. Traditional text analyzers, which rely on search methods for analyzing pre-selected content features, may not provide the desired conclusions. To address this issue, it is proposed to analyze the tonality of the text using an expanded dictionary of search features that covers a segment of correlated concepts. This approach was applied to speculative management of financial assets in day trading on the Forex market.

Keywords: *Multidimensional Non-Stationary Processes, Multi-Expert Control, Distributed Decision, Multi-Expert Asset Management, Knowledge Extraction.*

1. INTRODUCTION

A significant challenge in extracting messages from text analytical documents is the lack of clear and unambiguous information necessary for making forecasts and management decisions. Modern analysts, like ancient oracles, often use vague and ambiguous phrases that allow for multiple, often contradictory interpretations.

To address this issue, a milder form of text analysis is proposed for knowledge extraction. Instead of identifying exact information necessary for making management decisions, the general tonality of the target knowledge segment containing the control object is identified [1-3].

This paper considers trading in the Forex market as an example. The main sources of information are analytical studies formed by financial experts using fundamental market analysis. The traditional task of trading is proactive management of a financial instrument, based on forecasts of changes in the quotes of the selected instrument within a prediction time interval.

It is assumed that information about the projected price dynamics of financial instruments is contained in text documents. The goal is to automatically extract this information using Text Mining technologies [4-10]. If the required information cannot be explicitly detected and extracted, it is proposed to switch to document sentiment analysis (Opinion Mining), which allows assessing the general mood of statements regarding a certain market segment that includes the working instrument. Market segmentation is proposed to be based on selecting groups of working instruments with strong correlations to the working financial instrument.

Identifying a group of statistically related instruments allows for expanding the vocabulary of keywords used in selecting proposals. As a result, the mood of an entire market segment is assessed, reflecting useful information about a working instrument related to the selected segment with some probability. In other words, an expanded dictionary of key word forms makes it possible to identify knowledge that reflects the predicted tonality of the market segment and make a probabilistic conclusion about the possible direction of evolution of the value of a working financial instrument.

This approach allows for flexible selection of a working instrument based on its similarity to the average characteristics of the dynamics of the market segment. Market segmentation can be implemented on various grounds, with one effective option being

Journal of Theoretical and Applied Information Technology

15th November 2023. Vol.101. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

based on assessing the degree of correlation between quotes of financial instruments. However, such assessments can be unstable at short observation intervals in an unstable environment and using estimates obtained over long observation intervals can lead to erroneous forecasts due to natural fluctuations in correlations between quotes of instruments related to the selected market segment.

This approach has three important advantages:

1) Market segmentation based on correlations allows for the use of specific hedging technology: By using multiple instruments simultaneously, it is possible to level out occasional fluctuations in the dynamics of an individual instrument. This can help reduce the risk associated with trading in the Forex market and improve the accuracy of forecasts and management decisions.

2) Segmentation provides a convenient mathematical infrastructure for forming solutions based on multi-regression assessment of the market value of the working asset: This approach, as described in [11-12], allows for the use of advanced mathematical techniques to assess the market value of a working financial instrument. By using multi-regression analysis, it is possible to take into account multiple factors that may affect the price dynamics of a financial instrument and make more accurate forecasts.

3) Segmentation allows for the use of market tonality assessment when building a multi-expert decision-making system (MES): By assessing the general mood of statements regarding a certain market segment, it is possible to identify the predicted tonality of the market segment and make a probabilistic conclusion about the possible direction of evolution of the value of a working financial instrument. This information can be used when building a MES [13], which can help improve the accuracy of forecasts and management decisions.

2. METHODS

2.1 Data model

In [14-18], the description of financial instrument quotation observation series was justified using the Wold additive model:

$$y_k = x_k + v_k, \quad k = 1, \dots, n, \tag{1}$$

where $x_k, k = 1, \dots, n$ is a smoothed system component used to build control strategies, and a $v_k, \quad k = 1, \dots, n$ is a noise component. The set of observations for a group of financial instruments forming a market segment is characterized by a vector process. This means that the data for each instrument in the group is represented as a vector, with each element of the vector representing an observation at a specific point in time. The vectors for all instruments in the group are then combined to form a matrix, where each row represents an currency instrument and each column represents an observation at a specific point in time. This matrix can then be analyzed using various statistical and machine learning techniques to extract useful information about the market segment as a whole:

$$Y_k = X_k + V_k, \quad k = 1, \dots, n, \tag{2}$$

where $Y_k = \{y_{jk} = x_{jk} + v_{jk}, \quad j = 1, \dots, m\}, \quad k = 1, \dots, n$ is the observation vector formed in the process of monitoring the state of the market, m is the dimension of the market segment.

In this observation model, the system component is formed by an oscillatory non-periodic process, characteristic of dynamic chaos [19-24]. The noise component $v_k, \quad k = 1, \dots, n$ is a non-stationary random process approximately described by a Gaussian model with varying parameters [16, 25].

Figure 1 shows two examples of EURUSD currency pair quotations at 10-day observation intervals as illustrations confirming the chosen model.

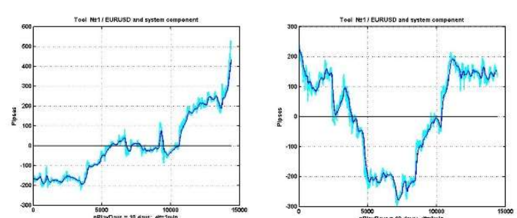

Figure 1. Quotes of the EURUSD currency pair at two 10-day intervals with the identification of the system component using exponential filtering

To isolate the system component, an exponential filter determined by the following equation was used:

$$x_k = \alpha y_k + (1-\alpha) y_{k-1} = x_{k-1} + \alpha (y_k - x_{k-1}), \quad k = 2, \dots, n, \tag{3}$$

with a smoothing coefficient $\alpha = 0.01 - 0.3$.

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2.2 Market segmentation methodology based on correlation analysis of dynamic relationships between financial instruments

In the chaotic dynamics of quotations, there are fairly stable patterns associated with the multidimensionality of trading processes. For example, with an increase in the observation interval, it is possible to detect fairly stable correlations between various instruments of the currency and other markets [12, 26].

Figure 2 illustrates this by showing time-synchronized charts of quotations for the EURUSD currency pair (black line) and five different currency instruments selected by their degree of correlation over an 85-day observation period. Visually, one can assess the high level of correlation between these processes.

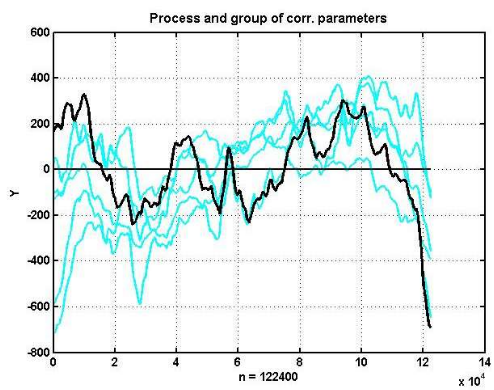


Figure 2. The process of changing the quotes of the EURUSD currency pair and the five most correlated quotes of currency instruments with it.

Figure 3 shows a tonal matrix reflecting the values of estimates of paired correlation coefficients over the same observation interval for 16 currency pairs numbered as follows: #1: EURUSD, #2: EURJPY, #3: EURGBP, #4: EURCHF, #5: EURCAD, #6: USDCAD, #7: USDCHF, #8: USDJPY, #9: GBPCHF, #10: GBPJPY, #11: GBPUSD, #12: AUDJPY, #13: AUDUSD, #14: CHFJPY, #15: NZDUSD, #16: NZDJPY.

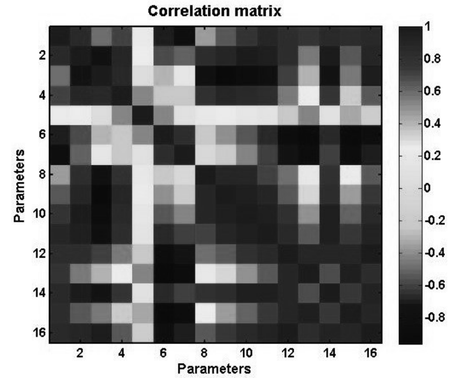


Figure 3. Tonal representation of the correlation matrix of 16 financial instruments

Figure 4 shows the same tonal matrix for the pair correlation coefficients of the EURUSD currency pair and 5 other currency pairs with the highest degree of correlation with this instrument: (#11: GBPUSD, #14: CHFJPY, #16: NZDJPY, #2: EURJPY, #12: AUDJPY). These instruments were used in constructing the graphs of joint changes in quotations shown in Figure 2.

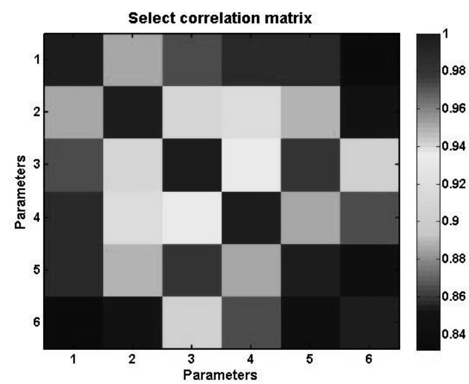


Figure 4. Tonal representation of the correlation matrix for the EURUSD currency pair and 5 other currency pairs with the highest degree of correlation with this instrument.

The presence of relations with lower variability of paired correlation coefficients than the quotations of working assets themselves allows for the formation of a market segment characterized by a high level of correlation among the financial instruments included in it. In the example considered, this means that when selecting documents and segmenting individual sentences, an extended dictionary of correspondences is proposed to be used, which includes a set of basic word forms (EURUSD, GBPUSD, CHFJPY, NZDJPY, EURJPY, AUDJPY) and text forms derived from them.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Further, using search (by a set of keywords) or statistical (by the frequency of characteristic word forms) knowledge extraction technologies [4-6, 27] , word forms corresponding to clusters of variants of the dynamics of market asset quotations are distinguished. The resulting conclusion will primarily relate to the tone of the expected market situation. To conclude on the nature of the dynamics of a particular financial instrument, it is advisable to carry out additional studies taking into account the results of technical analysis of an observation series.

It should be noted that at limited observation intervals, correlations between financial instruments in conditions of unstable market dynamics are also unstable. Figure 5 shows graphs of changes in values of estimates of paired correlation coefficients between two correlated currency instruments with an increase in the size of a sliding observation window (L = 10, 25, 50 and 75 counts). A sliding observation window is understood as a matrix of a data group:

$Y(\Delta_k) = (y_1(\Delta_k),\dots,y_n(\Delta_k))$, where $\Delta_k = (k - L,\ k)$, $k = L + 1,\dots,n$, and L is the window size.

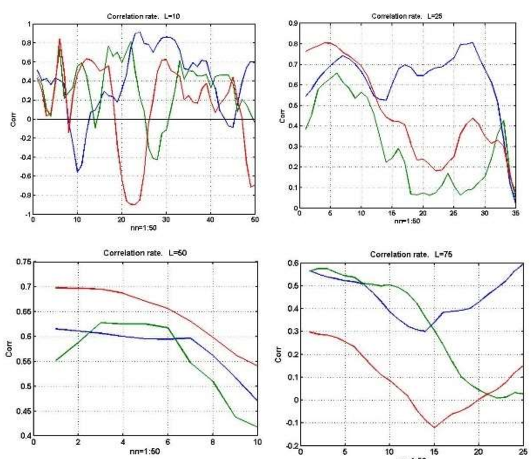


Figure 5. Estimation of the paired correlation coefficient between two currency instruments with the size of the sliding observation window L = 10, 25, 50 and 75 counts

Figure 5 shows how the estimation of the paired correlation coefficient between two currency instruments becomes more stable as the size of the sliding observation window increases. However, for the current selection of the basic word form dictionary used in the task of collecting documents and sentences, it is advisable to choose financial instruments with the highest correlation estimate obtained on a relatively small sliding observation window. This technology allows for adapting the composition of basic word forms to current changes in relational dynamics and improving the quality of text document tonality assessment.

In a technical sense, this adaptation involves step-by-step recalculation of the market instrument correlation matrix. In the example above, this means consistently assessing the correlation matrix of the 16 currency pairs presented. From the resulting matrix, a row corresponding to the number of the working tool is selected and ordered in descending order of paired correlation modulus values. Observations of the obtained variation series from the 2nd to the (m+1)th determine the group of financial instruments with the largest modulus values of correlations. The corresponding results obtained for 24 non-overlapping 10-hour observation intervals are presented in Table 1.

From the data presented, it can be seen that during the first seven observation intervals, the optimal group of instruments (1, 9, 8, 10, 16) did not change. At steps 8-10, the composition of the group was also preserved, but the first and ninth instruments changed places, which did not affect the choice of the base group of word forms.

Table 1. Lists of currencies ordered in descending order of correlation on non-overlapping observation intervals lasting 10 hours

Observation intervals	Regressor's numbers
1-7	1 9 8 10 16
8-10	9 1 10 8 16
11	9 10 1 8 16
12-14	9 8 10 16 1
15-17	9 8 10 16 1
18-19	8 9 10 16 4
20-21	8 9 10 4 16
22-24	9 8 10 4 16

The data presented in the table shows that the composition of the group of regressors evolves over time. However, the composition of the group of financial instruments changes quite slowly, and a 10-day adaptation interval is quite acceptable for forming the composition of the group of basic instruments used for presenting documents and relevant proposals in these documents.

The general conclusion is that the correlation selection scheme proposed in this section allows for significantly expanding the vocabulary of key word forms used for selecting documents and sentences in

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

documents. However, the knowledge (solutions) revealed as a result of knowledge extraction will not relate to a specific instrument, but will reflect the mood or tone of the market segment to which this instrument belongs. Therefore, the greatest effectiveness from using tonality estimation technology can be expected only in combination with other methods of forecasting the evolution of financial instrument quotations.

An example of a technology for forming a control solution based on processing information from heterogeneous sources is multi-expert data analysis [13,28]. In the next section, we will consider an example of implementing this approach by building a multi-expert system based on heterogeneous sources of information.

3. EXPERIMENT

Let's consider building a multi-expert system (MES) with three heterogeneous working software experts (PE) generating recommendations or draft solutions for managing a financial asset, and an supervisor forming the final decision. The first two PE are based on two alternative versions of channel strategies, which are described in well-known monographs on managing market assets in investments and trading [29-33]. The main idea of channel strategies is to form asset management recommendations based on the localization of the current asset value relative to a certain range (or "channel") of possible quotation value changes. Channels are often understood as areas of price changes with an a priori selected width parallel to the smoothed line of average quotation dynamics.

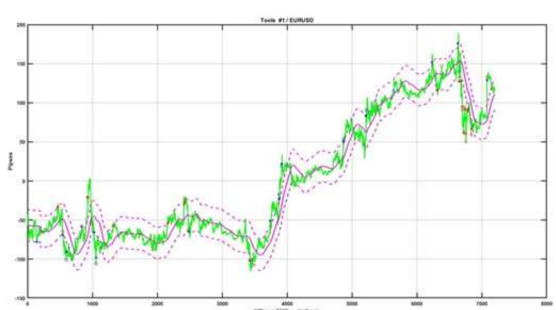
Let's consider an example of building a multi-expert system (MES) with three heterogeneous working software experts (PE) generating recommendations or draft solutions for managing a financial asset, and an ex-supervisor forming the final decision. The first expert, PE1, implements a control strategy based on interpreting the exit of the observed process beyond the channel boundary as a trend occurrence. In this case, a decision is made to open a position in the direction of the corresponding trend.

In contrast, PE2 is based on an alternative hypothesis, according to which the output of an asset's quotation trajectory beyond a set threshold is considered as a random fluctuation of its price. In this case, the inertia of market pricing will turn the trajectory in the opposite direction. This approach forms a recommendation to open a position in the opposite direction to the revealed local trend and to close it when the quotation reaches the level of the so-called "fair price" or according to other rules.

The third expert, PE3, belongs to the service layer and is a text analyzer focused on extracting information about the mood (tonality) of the market from text analytical reviews. Essentially, the task is to transform the content of existing analytical reviews prepared by specialists in fundamental market analysis into a fuzzy solution from an a priori given group of possible outcomes. Let's consider a simplified version of the extracted knowledge with three possible outcomes: 1) "the observed market segment has a positive mood (tone) and on average tends to increase the price of its assets"; 2) "the observed segment of the market has a negative mood and on average tends to decrease the price of its assets"; 3) "the observed segment of the market does not have a pronounced mood and is on average prone to flat, i.e., limited fluctuations in the prices of related assets within a given channel."

The supervisor receives recommendations on asset management from PE1 and PE2 experts in the form of commands for opening and closing positions, service information from PE3, and forms final versions of management solutions based on the data obtained. The supervisor's algorithm is to use the recommendations of PE1 if, according to PE3, a positive or negative mood of the market segment is expected that coincides with these recommendations. In contrast, when PE3 predicts the absence of a pronounced trend, the supervisor forms decisions based on PE2's recommendations.

For comparison, trading was simulated on an interval of quotation changes with a length of 5 days using real quotes of the EURUSD currency pair. Three management options were considered: based on separate use of PE1 and PE2's recommendations and, in the third case, based on MES described above.



ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

An example of MES-based management is shown in Figure 6.

Figure 6. An example of an asset management process based on a multi-expert system

The green line in Figure 6 represents the trajectory of the quote changes, while the solid crimson line is formed by an exponential filter with a velocity correlation. Correction is necessary because an exponential filter with a large transmission coefficient provides insufficient smoothing, and decreasing the value of this coefficient leads to a delay in the smoothed curve. Speed correction allows for satisfactory smoothing while significantly reducing the degree of lag.

Dotted lines define a "corridor" within which quote fluctuations can be considered to not contain an explicit trend. The RMS value of such fluctuations relative to the exponential mean lies in the range of $s(\delta\tilde{Y}_k) = 15 - 25$p. (points). In this example, a corridor width of 40 points was used. The position was closed at a level $dL = 20$p. from the opening level in both directions. Asterisks indicate the moments of opening a position, winning lozenges, and losing stops with circles.

Table 2 compares trading results for the three indicated options. It can be seen that independent use of PE1 or PE2 leads to a losing result. However, when using MES, it is possible to form a management strategy from two losing recommendation streams that has a generally winning result. The use of sequential evolutionary optimization, as described in [34,35], allows for increasing the gain by another 5-8%.

Table 2. Comparison of trading results for PE1-2 and MES

Method	Gain	Probability to Win	Average Win	Average Loss
PE1	-84	0.47	35.5	-34.7
PE2	-36	0.50	34.7	-35.5
MES	14	0.53	34.1	-32.3

It should be pointed out that the given example cannot serve as proof of the guaranteed advantage of the MES. In conditions of chaos, there is nothing guaranteed at all. In this example, the recommendations formed by expert analysts in the form of text reviews were used as service information, which, in turn, were correctly extracted by the PE based on the knowledge extraction search technology [27]. In general, the correctness of the results of fundamental analysis is not guaranteed.

On the other hand, for clarity, the most primitive versions of trading robots were used as PE1 and PE2. The use of more complex PE variables, for example, based on multi-regression analysis of markets with sequential correction of statistical estimates of financial instrument costs using evolutionary modeling or artificial neural networks, will significantly increase the efficiency of the MES. In addition, a significant potential for improving the MES is contained in modern technologies for jointly processing expert recommendations based on conflict and compromise theory [36,37]. These issues, as well as the development of the theoretical foundations of the MES, are the subject of further research.

4 Discussion

The general problem of managing a specific implementation of a process in unstable immersion environments currently has no effective solutions. This result is due to the chaotic nature of observed processes and corresponding observation series. The nature of dynamic chaos is due to instability of solutions, where even small variations in initial conditions lead to radical changes in process dynamics. An additional and significant complication for effective management is the presence of a purely random non-stationary component in observation series. In essence, the resulting process has the character of stochastic chaos. The compositional model (1), taking into account the description of its components, allows for a sufficiently visual interpretation of ongoing processes. However, ultimately it is not interpretation that is important but quality of forecasting and corresponding management efficiency. Therefore, it is quite acceptable to consider observation series as a single non-stationary random process if this will improve management effectiveness.

It should be noted that instability is also characteristic of many physical and technical systems. In these cases, an integral solution is often formed in the form of average dynamics that determines main trends of observed processes. For example, for a turbulent river flow independent from local rotors and countercurrents, main flow will always be determined by gravitational direction. With regard to electronic capital markets and speculative trading tasks, this approach is only acceptable in rare cases when news information indicates emergence of a pronounced trend.

In trading processes we are usually talking about working with a specific financial instrument or portfolio of such instruments. By analogy with turbulent flow we are talking about predicting movement of some particle or localized jet in chaotic motion. Such statement significantly complicates problem being solved and generally does not have terminal solution at all.

Currently main approach to solving problem of speculative asset management is combination of fundamental and technical analysis technologies. Trader gets acquainted with current analytics based on fundamental analysis and news information then closely follows current dynamics of working instrument quotes. Control decision is formed based on total flow information coming to trader and their own experience in trading operations.

The use of trading robots, or mechanical trade systems, has been increasing in recent years. These systems mainly rely on technical analysis to form control solutions. However, the incorporation of high-quality analytical forecasts into these trading robots could potentially improve the quality of the generated solutions. The challenge lies in automatically extracting knowledge from poorly structured textual information, particularly when information is presented in a latent form. This can be intentional, as a means of self-defense for experts in cases when their forecasts turn out to be erroneous, or due to the inability of individual experts to clearly formulate their thoughts. As a result, this type of analytics is gradually becoming more prevalent.

5 CONCLUSION

The paper discusses the technology of extracting knowledge from a certain set of analytical messages containing the required information in a latent form. In this case, it is proposed to move from directly predicting the dynamics of quotations of a particular financial instrument to assessing the mood of a market segment containing a working instrument. As a mechanism for forming a market segment, selection based on correlation analysis of a set of observed financial instruments is proposed.

It is quite clear that this approach is not a universal recommendation for all cases and contains a number of serious problems. For example, local fluctuations typical of chaos can lead to local de-correlation of the average dynamics of the market segment and the direction of movement of the quotation of a working financial instrument, leading to an erroneous recommendation in forming management.

This leads to the conclusion that it is expedient to use the considered approach as one program expert in a distributed system for forming knowledge based on hierarchical information interaction among a group of heterogeneous experts. Experts can be software implementations of data analysis algorithms or people.

The example given in the article, despite its simplified form, shows the significant potential of distributed information systems for decision support systems, which allows solving many problems related to big data problems. This approach is particularly important in tasks involving joint analysis of heterogeneous and poorly structured data (Data Fusion). In particular, it is expected that positive results will be obtained in tasks that have not yet been solved, such as predicting the state of unstable environments, managing multidimensional chaotic processes, etc.

6 ACKNOWLEDGMENTS

The research of Alexander Musaev described in this paper is partially supported by state research FFZF-2022-0004. Dmitry Grigoriev research for this paper was supported by the Center for Econometrics and Business Analytics and the Endowment Fund of St Petersburg University. The authors are grateful to participants at the Center for Econometrics and Business Analytics (ceba-lab.org, CEBA) seminar series for helpful comments and suggestions.

REFERENCES

[1] X. Man, T. Luo, J. Lin, *Financial sentiment analysis (fsa): A survey*. In 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS) (pp. 617-622), 2019.

[2] K. Ravi, V. Ravi, *A survey on opinion mining and sentiment analysis: tasks, approaches and applications*. Knowledge-based systems, *89*, 14-46, 2015.

[3] D. M. E. D. M. Hussein, *A survey on sentiment analysis challenges*. Journal of King Saud University-Engineering Sciences, *30*(4), 330-338, 2018.

[4] H. Hassani, C. Benek, S. Unger, M. T. Mazinani, M. R. Yeganegi, *Text mining in big data analytics*. Big Data and Cognitive Computing, 4(1), 1, 2020.

[5] T. Jo, *Text mining* (Vol. 45). Cham, Switzerland: Springer International Publishing, 2019.

[6] J. Fan, A. Kalyanpur, D. C. Gondek, D. A. Ferrucci, *Automatic knowledge extraction from documents*. IBM Journal of Research and Development, 56(3.4), 5-1, 2012.

[7] P. Clark, P. Harrison, *Large-scale extraction and use of knowledge from text*. In Proceedings of the fifth international conference on Knowledge capture (pp. 153-160), 2009.

[8] F. Harrag, *Text mining approach for knowledge extraction in Sahîh Al-Bukhari*. Computers in Human Behavior, *30*, 558-566, 2014.

[9] A. A. Musaev, D. A. Grigoriev, *Extracting knowledge from text messages: overview and state-of-the-art*. Computer Research and Modeling, 13(6), 1291-1315, 2021.

[10] O. Hassanzadeh, D. Bhattacharjya, M. Feblowitz, K. Srinivas, M. Perrone, S. Sohrabi, M. Katz, *Causal knowledge extraction through large-scale text mining*. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 34, No. 09, pp. 13610-13611), 2020.

[11] A. Musaev, A. Makshanov, D. Grigoriev, *Numerical studies of channel management strategies for nonstationary immersion environments: EURUSD case study*. Mathematics, 10(9), 1408, 2022.

[12] A. Musaev, A. Makshanov, D. Grigoriev, *Statistical analysis of current financial instrument quotes in the conditions of market chaos*. Mathematics, 10(4), 587, 2022.

[13] A. Musaev, D. Grigoriev, *Multi-expert systems: Fundamental concepts and application examples*. Journal of Theoretical and Applied Information Technology, 100(2), 336-348, 2022.

[14] M. Ayitey Junior, P. Appiahene, O. Appiah, C. N. Bombie, *Forex market forecasting using machine learning: Systematic Literature Review and meta-analysis*. Journal of Big Data, 10(1), 9, 2023.

[15] F. Jin, N. Self, P. Saraf, P. Butler, W. Wang, N. Ramakrishnan, *Forex-foreteller: Currency trend modeling using news articles*. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 1470-1473), 2013.

[16] A. A. Musaev, *Quod est veritas. Views transformation at a system component of observable process.* Informatics and Automation, *15*, 53-74, 2010.

[17] L. Bauwens, P. Giot, *Econometric modelling of stock market intraday activity* (Vol. 38). Springer Science & Business Media, 2001.

[18] I. K. Nti, A. F. Adekoya, B. A. Weyori, *A systematic review of fundamental and technical analysis of stock market predictions*. Artificial Intelligence Review, 53(4), 3007-3057, 2020.

[19] B. R. Andrievskii, A. L. Fradkov, *Control of chaos: methods and applications*. I. Methods. Automation and remote control, 64, 673-713, 2003.

[20] S. Wiggins, *Global bifurcations and chaos: analytical methods* (Vol. 73). Springer Science & Business Media, 2013.

[21] S. Ellner, P. Turchin, *Chaos in a noisy world: new methods and evidence from time-series analysis*. The American Naturalist, *145*(3), 343-375, 1995.

[22] D. Toker, F. T. Sommer, M. D'Esposito, *A simple method for detecting chaos in nature*. Communications biology, *3*(1), 11, 2020.

[23] J. Du, T. Huang, Z. Sheng, H. Zhang, *A new method to control chaos in an economic system*. Applied Mathematics and Computation, 217(6), 2370-2380, 2010.

[24] A. Musaev, E. Borovinskaya, *Prediction in Chaotic Environments Based on Weak Quadratic Classifiers*. Symmetry, *12*(10), 1630, 2020.

[25] S. P. Kothari, J. L. Zimmerman, *Price and return models*. Journal of Accounting and economics, 20(2), 155-192, 1995.

[26] A. Musaev, D. Grigoriev, *Analyzing, modeling, and utilizing observation series correlation in capital markets*. Computation, 9(8), 88, 2021.

[27] A. K. Nassirtoussi, S. Aghabozorgi, T. Y. Wah, D. C. L. Ngo, *Text mining for market prediction: A systematic review*. Expert Systems with Applications, 41(16), 7653-7670, 2014.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[28] S. Greco, J. Figueira, M. Ehrgott, *Multiple criteria decision analysis* (Vol. 37). New York: Springer, 2016.

[29] R. T. F. Nazário, J. L. e Silva, V. A. Sobreiro, H. Kimura, *A literature review of technical analysis on stock markets*. The Quarterly Review of Economics and Finance, *66*, 115-126, 2017.

[30] D. Iskrich, D. Grigoriev, *Generating long-term trading system rules using a genetic algorithm based on analyzing historical data*. In 2017 20th Conference of Open Innovations Association (FRUCT) (pp. 91-97). IEEE, 2017.

[31] P. S. Balagurin, A. V. Grigorieva, M. Kulagin, *Predicting changes in the state of an industrial facility using machine learning methods*. In AIP Conference Proceedings (Vol. 2402, No. 1). AIP Publishing, 2021.

[32] E. E. Peters, *Chaos and order in the capital markets: a new view of cycles, prices, and market volatility*. John Wiley & Sons, 1996.

[33] J. Gregory-Williams, B. M. Williams, *Trading chaos: maximize profits with proven technical techniques* (Vol. 161). John Wiley & Sons, 2004.

[34] A. Musaev, A. Makshanov, D. Grigoriev, *Evolutionary optimization of control strategies for non-stationary immersion environments*. Mathematics, 10(11), 1797, 2022.

[35] D. Simon, *Evolutionary optimization algorithms*. John Wiley & Sons, 2013.

[36] L. L. Davis, *Instrument review: Getting the most from a panel of experts*. Applied nursing research, 5(4), 194-197, 1992.

[37] C. C. Hsu, B. A. Sandford, *The Delphi technique: making sense of consensus*. Practical assessment, research, and evaluation, 12(1), 10, 2019.