ELIT
Economic Laboratory Transition
Research Podgorica

Montenegrin Journal of Economics

For citation:

Musaev, A., Makshanov, A., Grigoriev, D. (2023), "Dynamic Robustification of Trading Management Strategies for Unstable Immersion Environments", *Montenegrin Journal of Economics*, Vol. 19, No. 1, pp. 19-30.

Dynamic Robustification of Trading Management Strategies for Unstable Immersion Environments

ALEXANDER MUSAEV[1], ANDREY MAKSHANOV[2]
and DMITRY GRIGORIEV[3] (***corresponding author***)

[1] Professor, St. Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences, Saint-Petersburg State Institute of Technology (Technical University), 190013, St. Petersburg, Russia;
e-mail: amusaev@technolog.edu.ru
[2] Professor, Department of Computing Systems and Computer Science, Admiral Makarov State University of Maritime and Inland Shipping, 198035, St. Petersburg, Russia; e-mail: andrey.makshanov@mail.ru
[3] Associate Professor, Center of Econometrics and Business Analytics (CEBA), St. Petersburg State University, 199034, St. Petersburg, Russia; e-mail:d.a.grigoriev@spbu.ru

ARTICLE INFO

Received March 11, 2022
Revised from April 09, 2022
Accepted June 10, 2022
Available online January 15, 2023

JEL classification: E26, O4, E1, C22.

DOI: 10.14254/1800-5845/2023.19-1.2

Keywords:

chaos processes;
unstable immersion environment;
observation series;
channel strategy;
numerical studies;
dynamic stability;
robustness.

ABSTRACT

The paper considers the problem of constructing channel management strategies for market chaos conditions. The nature of dynamic chaos violates the probabilistic-statistical paradigm's fundamental principle of experiment repeatability. Under these conditions, the traditional statistical methods of evaluation are not effective, and the generated management decisions are unstable. There is a need to create management strategies that produce effective decisions for a wide variety of dynamic characteristics of observation series generated by market chaos. In this article, we have considered two variants of such robustification using channel management strategies as an ex-ample. The first approach is based on the assumption that the optimal solution for the observation interval with the least favorable dynamics for this management strategy will produce solutions that are satisfactory at other observation sites as well. However, our numerical study does not confirm this assumption. Explanation is that optimization of parameters for highly dynamic segments with abrupt changes in the observed process produces degenerate decisions. The optimal control parameters corresponding to them are suitable only for a very narrow range of possible variations of the observed process. The second approach to the dynamic robustification of management strategies is based on searching for optimal parameters of the strategy on large observation intervals. It is assumed that at such observation intervals, chaos will demonstrate the most variants of local dynamics, and the found parameters will be adapted simultaneously to the most diverse variations in dynamic characteristics of observation series. In general, this approach gives an encouraging result, however, as expected, the decrease in performance in the non-matching data segment turned out to be significant.

INTRODUCTION

The main difficulty of asset management in the conditions of market chaos is the instability of the immersion environment (Gregory-Williams & Williams, 2004; Peters, 1996; Zhang & Cheng, 2003; de Wolff et al., 2020). The presence of dynamic chaos in the series of observations violates the fundamental premise of the probabilistic-statistical paradigm on the repeatability of experiments under identical conditions (Maknickienė et al., 2020). At the same time, in the process of asset management, geometrically similar observation segments correspond to completely different aftereffects (Zhang et al., 2020; Musaev et al., 2021). As a result, traditional forecasting and management techniques based on statistical data analysis approaches are ineffective (Abbasov & Karimov, 2020).

The practice of applying various management strategies in conditions of market chaos has shown that their implementation does not contradict the possibility of profitable decisions (Nie-derhoffer & Kenner, 2005; Colby & Meyers, 2012; Chordia et al, 2018; Kashif et al., 2020; Amoozad Mahdiraji et al. 2021). However, any optimized management is dynamically unstable. This means that even a small time shift of the observation area where management is carried out with fixed, previously optimized strategy parameters leads to unpredictable changes in the effectiveness of the management process.

Hence, the task arises to analyze the stability of management strategies in the conditions of market chaos and to discover ways of constructing their robust versions having increased resistance to variations in dynamic and statistical characteristics of the observed process.

1. MATERIALS AND METHODS

As a basis for modeling market asset quotes, we are to use Wald's additive model [Musaev et al., 2021]:

$y_k = x_k + v_k$, $k = 1,\dots,n$, (1)

where x_k, $k = 1,\dots,n$ is a system component estimated by sequentially smoothing the time series of initial observations y_k, $k = 1,\dots,n$ and are to be used in the process of making management decisions, and v_k, $k = 1,\dots,n$ is the noise component.

Traditional models of statistical data analysis made it possible to construct a wide class of control strategies based on various hypotheses on dynamic properties of observation series [Nie-derhoffer & Kenner, 2005; Chordia et al., 2018]. However, each management strategy of that sort is effective only in a narrow range of possible dynamic variations of quotations. The underlying reason for the low efficiency of the various management strategies stems from the fundamental discrepancy between the traditional statistical approach and the nature of real observations. The market asset observation series' significantly differ from traditional statistical models by following features:

- their system component x_k, $k = 1,\dots,n$ is an oscillatory nonperiodic process with a large number of local trends. This description indicates the possibility of modelling this process as an implementation of some dynamic chaos models [Guanrong, 2021; Gardini et al., 2020; Davies, 2020; Jun, 2022].
- the noise v_k, $k = 1,\dots,n$ is a nonstationary random process approximately described by the Gaussian model with fluctuating parameters. At the same time, noise variations contain local trends, and their correlation characteristics change significantly over time (Musaev et al., 2021; Musaev and Grigoriev, 2021).

In order to isolate the system component, any technique of sequential filtration can be applied. In the simplest case, an exponential filter is used for this purpose, defined as (Gardner, 1985):

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

with a smoothing coefficient α, whose value most often lies in the range $[0.01,\ 0.3]$.

These characteristics violate the conditions of applicability of traditional statistical methods for effective decision-making. Moreover, violation of repeatability under similar conditions prohibits any prior analytical assessments of forecasts and corresponding proactive management strategies. In essence, the main method of analyzing the quality of asset management in this case is numerical studies that assess the effectiveness of management algorithms over long observation intervals.

A management strategy is understood as a functional S: Y ⟶ U that maps a set of current and retrospective observations $Y_k = (y_1, ..., y_m)_k$, k = 1,...,m to the set of acceptable management decisions $U_j = (u_1,...,u_M)$, j = 1,...,M, where M is the number of asset management operations.

The task of a trader or a trading robot is to choose a management strategy S and form a corresponding sequence of actions u_j, j = 1,...,M that provides maximum profit

$$R(S) = \sum_{j=1}^{M} \Delta y_j = \sum_{j=1}^{M} y_j\,(k_{close}) - y_j\big(k_{open}\big) = \max \qquad (3)$$

where $\Delta y_j = y_j(k_{close}) - y_j(k_{open})$, j = 1,...,M, is the effectiveness of the j-th operation, determined by the difference between the states of the asset at the interval of opening and closing the position. The difference in management strategies consists in the way to determine the time moments of time $(k_{open}, k_{close})_j$, j = 1,...,M, and, in some cases, the size of the lot. If the resulting amount at some k-th step turns out to be less than the trader's available deposit R_0, it means a complete loss.

As an example to illustrate the stable asset management technologies considered in the article, let us consider channel management strategies (Niederhoffer & Kenner, 2005; Chordia et al., 2018). The choice of this class of strategies is driven by their simplicity and clarity, which make it easy to visualize and interpret the obtained results and conclusions.

Let y_k, k = 1,...,n be a time series of observations on changes in the value of a financial asset used in trading or investment tasks. The term "channel" in the simplest case refers to the range of observations limited by a range $y_k = x_k \pm B$, k = 1,...,n, where x_k, k = 1,...,n is the system component of a observations segment. The segment is usually formed by a smoothing filter and used in the process of developing management decisions. Variations of observations in regard to the system component inside $|y_k - x_k| = |\delta y_k| \le B$, k = 1,...,n, are interpreted as fluctuations that do not contain a pronounced trend. The process itself is sometimes called a *sideways trend* or a *flat*. The choice of the channel width B can be driven by various considerations. It usually lies in the $(1 - 3)s_y$ range, where s_y is the estimate of the *standard deviation* (SD) of the noise in model (1) $v_k = \delta y_k = y_k - x_k$, k = 1, ..., n.

In general, the channel width is an option that depends on the features of the selected management strategy. In some cases, it can be a variable value $B_k = B_k(y_k)$, k = 1, ..., n.

The current value of a quotation y_k, k = 1,...,n breaking out of the channel can be interpreted as the emergence of a trend. In this case, the well-known management strategy of "playing by the trend" (CSF, "channel strategy, play forward") is used. This means the recommendation to open a position in the direction corresponding to the sign of the channel boundary.

An alternative version of the channel strategy proceeds from the assumption that the process going beyond the channel is a random fluctuation that is to be damped by market mechanisms of asset price correction. This approach employs the channel strategy of playing against the trend (CSB, "*channel strategy, play back*"). This means a recommendation to open a position in the direction opposite to the sign of the channel boundary.

In both cases, the position can be closed when a given level of profit (TP, "*take profit*") or loss (SL, "stop loss") is reached, or in accordance with other, more flexible rules defined by the management strategy.

The given simplified channel strategy makes it possible to remove many minor details. It makes the problem clear for the terminal task of producing stable management for the selected class of management strategies.

2. RESULTS

2.1 Simplest dynamic robustification of the CSB strategy

Traditional methods of robustification the statistical estimation and management algorithms are based on finding the best solution for the least favorable conditions (Huber, 1981; Baltas et al., 2018; Maronna et al., 2019). After that, the solutions are used for other observation segments, with more favorable conditions for the chosen management strategy. The price for the stability of robustified solutions is a significant decrease in effectiveness compared to the optimal version. In this case, we compare the achieved gain (3) with the potentially achievable one.

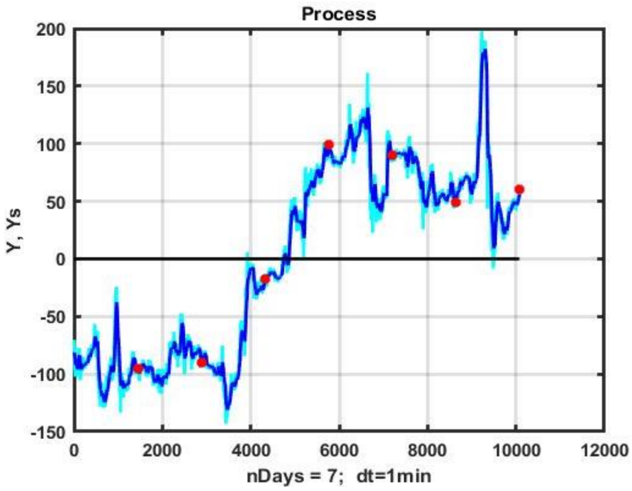


Figure 1. Change dynamics of quotations during seven observation days.

Source: Own

To investigate this issue, as an example of initial data, we consider a 7-day observation segment of the EURUSD quotation with one-minute counts. The corresponding plot is shown in Fig. 1, the separation between observation days is indicated by red circles.

Table 1 shows the performance R* of the best solutions and their corresponding parameters (α*, B_{Dn}*, B_{Up}*, TP*, SL*) of the CSB channel strategy. Optimization was carried out by bruteforcing their values with ranges and steps, respectively, being, α = 0.01:0.01:0.15, B_{Dn}, B_{Up}=5:1:15, TP, SL=7:1:15.

Table 1. Best solution performance

Day	R*, p.	α^*	B^*_{Dn}, p.	B^*_{Up}, p.	TP*, p.	SL*, p.
1	174	0.03	10	10	16	13
2	164	0.03	7	6	11	12
3	82	0.02	8	5	16	15
4	169	0.06	5	9	8	16
5	176	0.01	10	13	21	7
6	186	0.09	9	6	14	18
7	129	0.02	11	5	21	16

Source: Calculation by Author

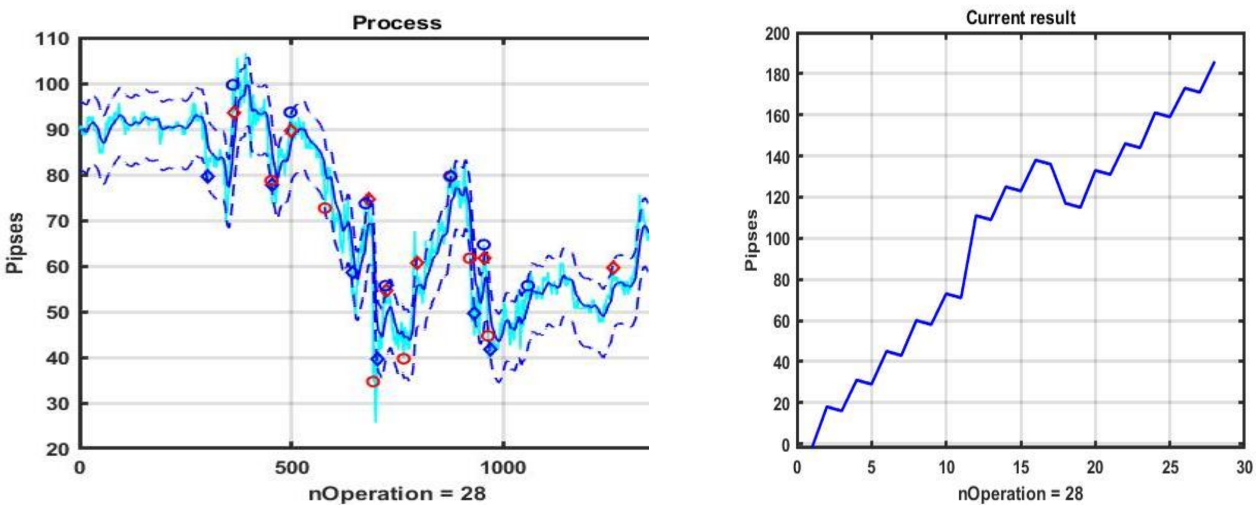
Comparing the values given in Table 1 with the plots in Figure 1, we can draw the expected conclusion that this strategy produces the best result in the observation segments tending to a sideways trend. However, even such a trivial conclusion has exceptions. For example, for the observation 5th day, which contains sufficiently strong fluctuations in the quotations, with correctly selected parameters, it is possible to obtain R = 176p. as a result. It seems that this is due to relatively large values of the channel boundaries B_{Dn}, B_{Up}, which made it possible to avoid incorrect openings with strong, abrupt trends.

As examples, Figure 2 (a) shows plots illustrating the management process with the best parameter values of the sixth day of observation. This observation segment is characterized by relatively weak local trends. In the figure, blue diamonds indicate opening a position up, red ones indicate opening a position down, and circles of corresponding colors are the closings. Figure 2 (on the left) shows a graph of changes in management performance. The total result of the management was R = 186p. Figure 3 shows similar plots for the third day of observation, characterized by a strong positive trend and having the least significant result of R = 82p.

Let us clarify what the most unfavorable conditions for the use of this management strategy are. As already noted, for the CSB channel strategy, unfavorable areas are characterized by strong trends with abrupt corrections (the areas in Fig.1 corresponding to the 3rd and 7th days of observation).

Let us consider the question of the effectiveness of using the best option parameters for a particular observation day for other observation days. For this purpose, we use the previous example with a 7-day observation area. In Table 2, the diagonal shows the effectiveness of the CSB control strategy with optimal parameters, and the lines show the result of applying the strategy with these parameters for all seven days of observation.

According to the general theory of robust estimation (Huber, 1981; Baltas et al., 2018; Maronna et al., 2019), the most stable result may be expected when using the optimal parameters obtained for the least favorable, 3rd day of observations. However, it is not difficult to see that both for the most unfavorable dynamics of observations (observation days 3 and 7) and for other days, the use of optimal parameters leads, in most cases, to losses. The exception is a set of optimal parameters for the 6th day of observation $P^* = (\alpha^*, B_{Dn}^*, B_{Up}^*, TP^*, SL^*) = (0.09, 9, 6, 14, 18)$, characterized by relatively moderate variability and some slight negative trend.



a) b)

Figure 2. CSB management (a) and its result (b) with parameters that are found to be optimal for the 6th day of observation

Source: Own

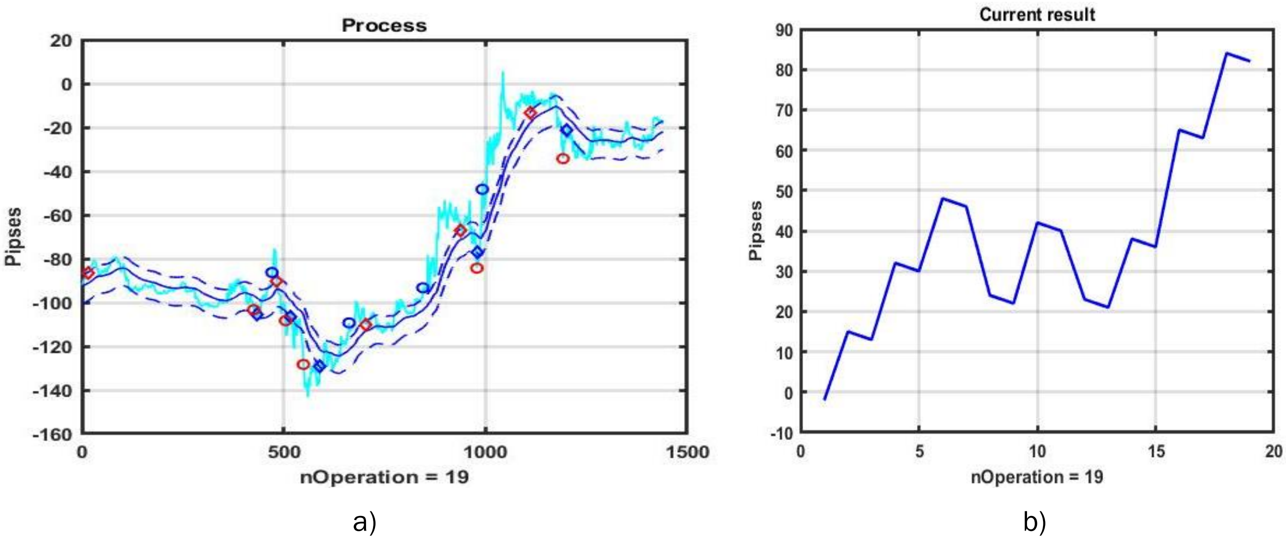


Figure 3. CSB management (a) and its result (b) with parameters that are found to be optimal for the 3rd day of observation

Source: Own

Table 2. Performance with optimal parameters for the corresponding days

Day	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1	**174**	21	−37	72	19	−5	44
2	17	**164**	96	0	−8	96	53
3	−56	−90	**82**	−96	−56	−40	−4
4	−36	−57	−121	**169**	−147	−57	−133
5	−35	−92	−64	−29	**176**	−52	−49
6	96	4	25	66	3	**186**	40
7	−12	−65	50	−87	−36	−228	**129**

Source: Calculation by Author

This set of parameters not only produced the best result among other vectors of optimal parameters for the corresponding days on which a posteriori optimization was carried out, but also ensured a gain, albeit small, on all seven days of observation. Its noticeable differences from other such vectors are the increased value of the exponential filter's transfer coefficient and an SL that slightly exceeds the other SLs (see Table 2). Of course, such an outcome may be random: it is not confirmed by the results of the 1st and 2nd observation days, which are also characterized by weak dynamics and have optimal parameters that produce gain over the entire 7–day observation interval.

In general, from the studies presented in this section, it can be concluded that the considered primitive robustification scheme is incapable to produce a stable positive result for the chosen management strategy. Moreover, the opposite result was obtained. Namely, the best set of options for the situations most favorable for the selected type of strategy, obtained the best result for the entire 7-day observation interval. Obviously, this conclusion cannot be accepted as reliable due to the limited size of the selected data polygon and requires confirmation with significantly large volumes of source data.

2.2 Dynamic robustification of the CSB based on optimal parametric solutions for large observation intervals

As an option of a channel management strategy with increased resistance to variations in the dynamic characteristics of observation series, consider a model with optimal parameters over a large observation interval. In the example, an observation interval of 15 days is considered (Figure 4). This area contains a multitude of quote variations: sideways trends with different levels of scope, areas of slow and abrupt growth and decline, impulse-like jumps, etc.

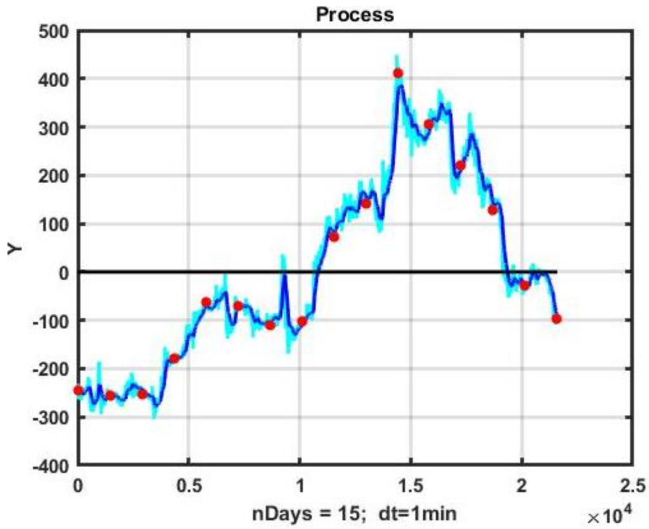


Figure 4. Change dynamics of quotations during 15 observation days.

Source: Own

We use bruteforce optimization on the values of optional parameters with ranges of variation α = 0.01:0.01:0.15, B_{Dn}, B_{Up}=5:1:15, TP, SL=7:1:15. In this case, the best result of using the CSB strategy was R=475p. with parameters P* = (α*, B_{Dn}*, B_{Up}*, TP*, SL*) = (0.02, 6, 8 , 17, 21). The performance of the management strategy with specified parameters at the selected observation interval is shown in Figure 5.

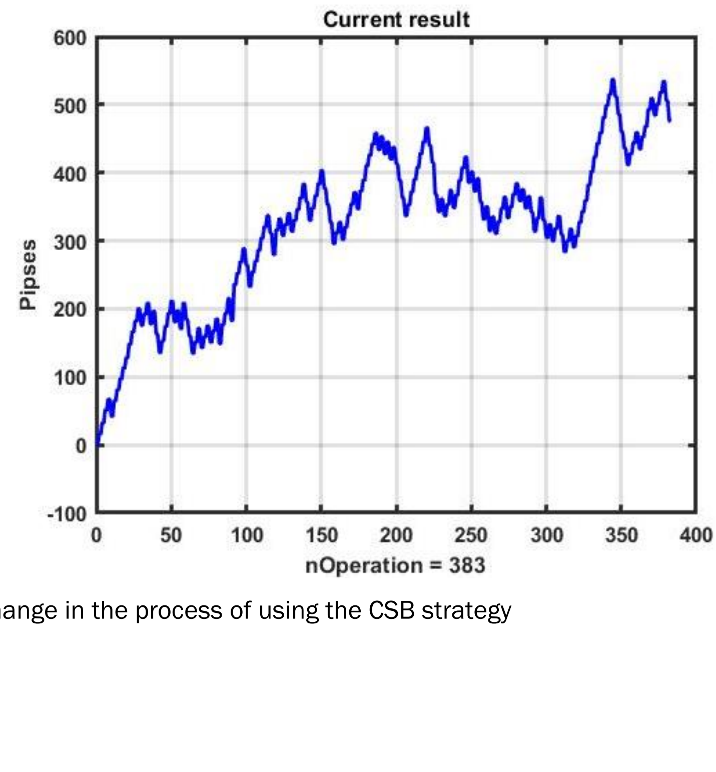


Figure 5. Performance change in the process of using the CSB strategy

Source: Own

Applying the found parameters of the management strategy separately to each of the observation days, we obtain a vector of results: R=(80, 101, 36, –59, 75, 49, –23, –4, 125, –102, 17, –7, 189, –2, –19). At the same time, the total result R_S = 456p is quite close to the previous result of optimizing for the entire 15–day observation area. Let us consider how effective the parameters P* are in the subsequent 10-day observation interval that does not intersect with the training data interval (Figure 6). The vector of one-day results in this case is R = (22, 49, 53, –7, –12, –20, 66, –51, 49, –98).

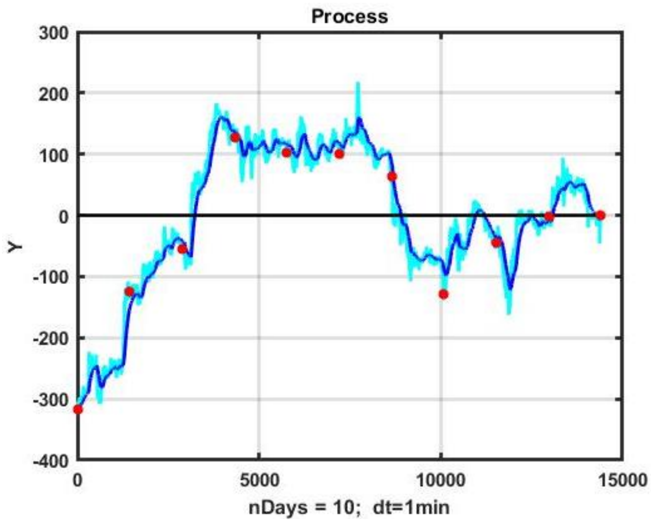


Figure 6. Quotation dynamics on a subsequent 10-day observation interval

Source: Own

Comparing obtained results with the dynamics of one-day processes (Figure 6), the following preliminary conclusions may be drawn:

- The application of the parameters of the CSB control strategy with optimal parameters estimated over a large training interval of observations significantly changes its initial properties. Namely, the best results were obtained in areas with highly linear dynamics (days 1, 2, 3, 7), and in areas with small linear trends (days 4, 5, 6), the strategy turns out to be losing.
- The effectiveness of the strategy is the most unpredictable for observation segments where the dynamics of the process move in the opposite direction (8-10 days).
- These examples, in general, confirm the a priori positive assumption about the applicability of the proposed scheme of dynamic robustification to the management strategy. At the same time, the negative assumption about the high cost of increasing the stability of management is also confirmed. This conclusion also needs further statistical studies on large datasets.
- In the process of parametric optimization of the control strategy, CSB acquired some properties that bring it closer to CSF. As a result, it is of interest to repeat the conducted studies for the CSF. The next section of the article is devoted to this issue.

2.3 Dynamic robustification of CSF

In accordance with the CSF management strategy, a position is opened up when the observed process y_k, k = 1,...,n crosses the level $x_k + B$, k = 1,...,n from the bottom up, or down when crossing $y_k = x_k - B$, k = 1,...,n from the top down. An example of its implementation on a one-day observation segment is shown in Figure 7. Here x_k, k = 1,...,n is the system component formed by an exponential filter (2) with α = 0.02. The remaining parameters were assumed to be equal to B_{Dn}, B_{Up} = 8, TP, SL = 17.

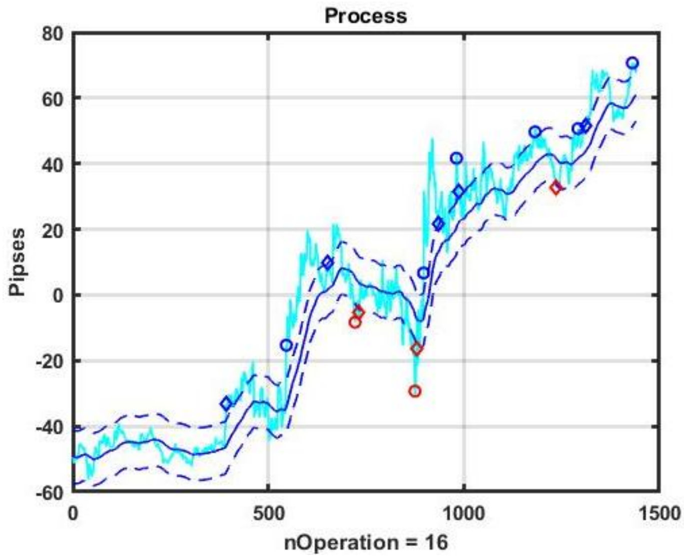


Figure 7. Example of CSF implementation on a one-day observation segment

Source: Own

We chose the same observation segment for the parametric optimization for a large interval of 15 days as for the CSB strategy (Figure 4), retaining the same set of ranges for optional parameters α = 0.01:0.01:0.15, B_{Dn}, B_{Up}=5:1:15, TP, SL=7:1:15. The best values of parameters P* = (α*, B_{Dn}*, B_{Up}*, TP*, SL*) = (0.1, 11, 14, 16, 13) are produced by bruteforce search.

The performance of the management strategy with the specified parameters at the selected observation interval is shown in Figure 8. The best result was *R=252* p., which is only 53% of the result of applying the CSB strategy with optimal parameters at the same observation interval.

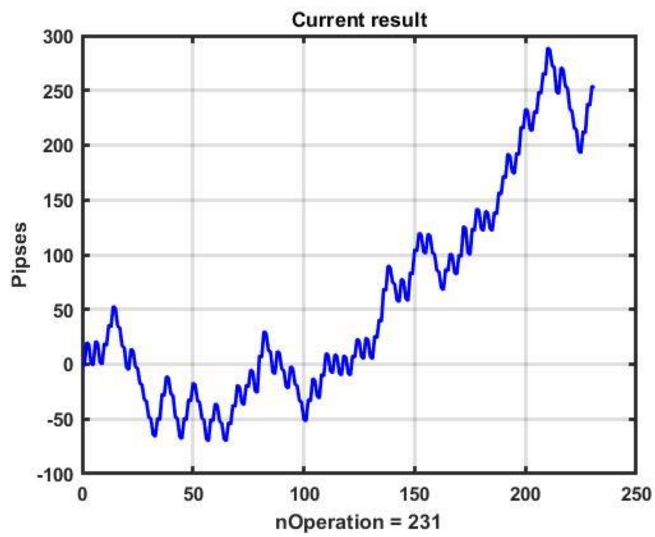


Figure 8. Performance for the CSF strategy with the best parameters

Source: Own

Following the proposed method of stability analysis of the obtained result, let us consider how effective the found optimal parameters are in the subsequent 10-day observation interval that does not intersect with the training interval (Fig. 6).

The vector of one-day results in this case is R = (–27, 64, –31, –71, –10, –107, –77, –75, –166, –34), which indicates low efficiency and pronounced dynamic instability of this management strategy.

DISCUSSION AND CONCLUSION

The problem of constructing management strategies that show stable performance in an unstable immersion environment with pronounced signs of dynamic chaos is essential in trading and investment.

This problem can be solved in several various ways. The obvious solution is the construction of a qualitative forecast regarding the dynamics of the observed process, but at present it is not effective due to the very nature of market chaos. The reason is the extremely high variability and lack of inertia of the observed processes, which obstructs the use of statistical extrapolation methods (Musaev and Grigoriev, 2022; Peng et al., 2018). Nevertheless, research in this direction continues, mainly focused on indirect analysis of multidimensional dynamic processes that takes into account correlation relationships and other features of large arrays of retrospective observations (Musaev et al, 2021; Musaev and Grigoriev, 2021).

Increasing the dynamic stability of management strategies may be provided by two primary approaches: adaptation and robustification, i.e. reducing their sensitivity to variations in the dynamic characteristics of the observed process.

The complexity of applying adaptive control methods in unstable immersion environments is associated with extremely rapid changes in the very structure of the observed processes. This fact is clearly visible in Fig. 1, 4, 6. As a result, the feedback loop in the process of adaptation does not keep up with the abrupt changes in quotations. Attempts to increase the speed of adaptation lead to a rapid response to dynamic fluctuations, which, in turn, causes an increase in statistical errors of type II ("false alarms"). Nevertheless, the question of the applicability of adaptive and self-organizing management strategies is worthy of independent research, which the continuation of this article will be dedicated to.

The problem of dynamic robustification (more precisely, robustification to variations of dynamic characteristics) is based on decrease in the sensitivity of control strategies to variations of the observed process. In this article, we have considered two variants of such robustification using channel management strategies as an example.

The first approach is based on the assumption that the optimal solution for the observation interval with the least favorable dynamics for this management strategy will produce solutions that are satisfactory at other observation sites as well. For the CSB strategy based on the hypothesis of trend absense, the most unfavorable are the observation areas with pronounced growth or decline. However, the experiment completely rejected this approach. The most stable result at seven observation segments was obtained by management with parameters optimal for the observation interval characterized by a slight negative trend. In other words, the best result for favorable conditions turned out to be quite satisfactory for other days of observation. This conclusion is also confirmed by the results of applying the optimal parameters of other observation days with dynamics close to a sideways trend.

This paradox can be explained by the statistical limitation of the number of experiments. Another, more convincing explanation is that optimization of parameters for highly dynamic segments with abrupt changes in the observed process produces degenerate decisions. The optimal control parameters corresponding to them are suitable only for a very narrow range of possible variations of the observed process. Any exit beyond this range quickly leads to a loss in management effectiveness.

The second approach to the dynamic robustification of management strategies is based on searching for optimal parameters of the strategy on large observation intervals. It is assumed that at such observation intervals, chaos will demonstrate most variants of local dynamics, and the found parameters will be adapted simultaneously to the most diverse variations in dynamic characteristics of observation series.

As an example, we consider a CSB management strategy with optimal parameters for a 15-day observation interval. The effectiveness of the found solution was validated at the subsequent 10-day observation interval. In general, this approach gives an encouraging result, however, as expected, the decrease in performance in the non-matching data segment turned out to be significant. This result is extremely important from a practical point of view and requires further research.

In conclusion, we note that the CSB channel strategy, which is based on the hypothesis that breaking through the channel boundaries is only a random fluctuation, has demonstrated a clear advantage over the alternative CSF strategy. Nevertheless, it should be remembered that both strategies were used to ensure the clarity of the drawn conclusions. For practical applications, it is advisable to use more complex modifications of these strategies, based, for example, on multi-channel, self-organizing, precedent and multi-expert computing schemes.

ACKNOWLEDGEMENTS

Dmitry Grigoriev research for this paper was supported by a grant from the Russian Science Foundation (Project No. 22-18-00588).

REFERENCES

Abbasov, J., Karimov, K. (2020), "Households survey and inflation expectation", *Economics and Sociology*, Vol. 13, No. 2, pp. 210-227. doi: 10.14254/2071-789X.2020/13-2/14

Amoozad Mahdiraji, H., Zavadskas, E.K., Arab, A., Turskis, Z., Sahebi, I.G (2021), "Formulation of Manufacturing Strategies Based on an Extended SWARA Method with Intuitionistic Fuzzy Numbers: an Automotive Industry Application", *Transformations in Business & Economics*, Vol. 20, No 2 (53), pp. 346-374.

Baltas, I., Xepapadeas, A., Yannacopoulos, A.N. (2018), "Robust portfolio decisions for financial institutions", *Journal of Dynamics & Games*, Vol. 5, No. 2, p. 61.

Chordia, T.; Goyal, A., Saretto A. (2018)," p-hacking: Evidence from two million trading strategies", *Swiss Finance Institute*, No. 17-37, http://dx.doi.org/10.2139/ssrn.3017677

Colby, R.W., Meyers, T.A. (2012), *The Encyclopedia of Technical Market Indicators*, IRWIN professional Publishing, Burr Ridge, IL.

Davies, B. (2018), *Exploring Chaos: Theory And Experiment (Studies in Nonlinearity)*, CRC Press, Boca Raton, FL.

de Wolff, T., Cuevas, A., Tobar, F. (2020), "Gaussian process imputation of multiple financial series" in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 8444-8448.

Feldman, D. (2019), *Chaos and Dynamical Systems*, Princeton University Press, Princeton, NJ.

Gardini, L., Grebogi, C., Lenci, S. (2020), "Chaos theory and applications: a retrospective on lessons learned and missed or new opportunities", *Nonlinear Dynamics*, Vol. 102, pp. 643-644.

Gardner, J.E.S. (1985), "Exponential Smoothing: The State of the Art", *Journal of forecasting*, Vol. 4, pp. 1–28.

Gregory-Williams J., Williams B.M. (2004), *Trading Chaos: Maximize Profits with Proven Technical Techniques*, 2nd ed., John Wiley & Sons: NY.

Guanrong, C. (2021), "Chaos theory and applications: a new trend", *Chaos Theory and Applications*, Vol. 3, No. 1, pp. 1-2.

Huber, P.J. (1981), *Robust Statistics*, John Wiley & Sons: New York, NY.

Jun, M.A. (2022), "Chaos theory and applications: the physical evidence, mechanism are important in chaotic systems", *Chaos Theory and Applications*, Vol. 4, No. 1, pp. 1-3.

Kashif, M., Chamadia, S., Raheem Ahmed, R., Kalugina, O.A., Havrysh, V. (2020), "Identifying Investment Strategies Using Accounting Information from Stock Market", *Transformations in Business & Economics*, Vol. 19, No 3 (51), pp. 235-260.

Maknickienė, N., Maknickas, A., Martinkutė-Kaulienė, R. (2020), "Trading support method based on computational intelligence for speculators in the options market", *Journal of International Studies*, Vol. 13, No. 3, pp. 231-247. doi: 10.14254/2071-8330.2020/13-3/15

Maronna, R.A., Martin, R.D., Yohai, V.J., Salibián-Barrera, M. (2019), *Robust statistics: theory and methods* (with R).,John Wiley & Sons, New York.
Musaev, A.A., Grigoriev, D.A. (2021), “Analyzing, Modeling and Utilizing Observation Series Correlation in Capital Markets”, *Computation*, Vol. 9, p. 98.
Musaev, A.; Grigoriev, D. (2022), “Numerical Studies of Statistical Management Decisions in Conditions of Stochastic Chaos”, *Mathematics*, Vol. 10(2), p. 226.
Musaev, A.A., Makshanov, A.V., Grigoriev, D.A. (2021), “Forecasting Multivariate Chaotic Processes with Precedent Analysis”, *Computation*, Vol. 9(10), p. 110.
Niederhoffer, V., Kenner, L. (2005), *Practical Speculation*, John Wiley & Sons: NY.
Peng, Y., Sun, K., He, S., Yang, X. (2018), “Parameter estimation of a complex chaotic system with unknown initial values”, *The European Physical Journal Plus*, Vol. 133, No. 8, pp. 1-13.
Peters, E.E. (1996), *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*; 2nd ed., John Wiley & Sons, NY.
Zhang, M.H., Cheng, Q.S. (2003), “Gaussian mixture modelling to detect random walks in capital markets”, *Mathematical and computer modelling*, Vol. 38, No. 5-6, pp. 503-508.
Zhang, N., Lin, A., Yang, P. (2020), “Detrended moving average partial cross-correlation analysis on financial time series”, *Physica A: statistical mechanics and its applications*, Vol. 542, p. 122960.