Model for Monitoring of Socio-Economic Processes Using Fuzzy Cognitive Map and Algorithms for Detecting Structural Changes

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Keywords: Monitoring, Structural Shifts, Sequential Analysis, Fuzzy Cognitive Map, Scenario Modelling, Time Series.

Abstract: The paper considers the model of monitoring conducted to detect structural shifts in socio-economic processes, arising under the influence of events in the external environment. The proposed procedure includes monitoring of the macro- and business environment in which the observed process develops; monitoring of time series describing the dynamics of the observed processes; supervisor for analysing signals from two monitoring systems, adjusting their parameters and forming the final output signal. The practical significance of the proposed procedure consists in increasing the efficiency of structural shift detection algorithms by obtaining additional information by them, and, accordingly, in enhancing the capabilities of expert-analysts and forecasters in solving the target problems of analysis and forecasting in situations of uncertainty and instability based on the processing of heterogeneous information.

1 INTRODUCTION

In control methodology, monitoring is one of the universal functions, necessary and applicable to any control object (technical, socio-economic, environmental, etc.). The relevance of this function is due, firstly, to the increased requirements for the control of objects of different nature, which are constantly becoming more complex, and secondly, to the need to account for rapid changes in the external environment, affecting the control object, the inconsistency of these changes and their interrelated nature. (Rychihina, 2008, Aita, 2020)

The description of the processes of functioning of social, financial and economic systems includes a set of time-varying numerical parameters. There is a need for timely detection of changes in the structure of process development under the influence of internal and external influences. Digital monitoring systems conducted to detect changes in time series of parameters called structural shifts have become widespread (e.g., Lazariv and Schmid, 2018, Pergamenchtchikov, Tartakovsky and Spivak, 2022).

However, the results of digital monitoring do not allow us to solve such tasks as: (i) forecasting the further development of the situation that led to the emergence of a structural shift and the signal of digital monitoring; (ii) forecasting the situation that may lead to a structural shift. To support the solution of these tasks, along with digital monitoring, it is necessary to develop situation monitoring tools based on the processing and analysis of expert information from heterogeneous sources in order to identify the causes of structural shifts in the observed processes, to gain an in-depth understanding of the situation, which will help the forecasting system to build appropriate forecasts. By situation monitoring, we mean dynamic tracking and evaluation of significant changes (events, phenomena) in a situation that characterizes the interaction of the observed process(es) in the functioning of the systems mentioned above with heterogeneous environmental factors affecting these processes. The emphasis on the processing of qualitative information in situation monitoring is due to the lack of quantitative data on the processes of functioning of these systems in conditions of rapid (turbulent) and poorly predictable changes in the external environment.

In this research, we present a model for organizing the joint situation and digital monitoring of socio-

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Avdeeva, Z., Grebenuyk, E. and Kovriga, S.
Model for Monitoring of Socio-Economic Processes Using Fuzzy Cognitive Map and Algorithms for Detecting Structural Changes.
DOI: 10.5220/0011949900003612
In *Proceedings of the 3rd International Symposium on Automation, Information and Computing (ISAIC 2022)*, pages 428-433
ISBN: 978-989-758-622-4; ISSN: 2975-9463

economic processes. The proposed monitoring procedure implements the following objectives: detection of structural shifts, identification of the causes that have led or may lead to the emergence of structural shifts, formation of scenarios for possible development of the situation, assessment of the power and duration of upcoming changes.

Situation monitoring is aimed at identifying information about significant changes in the external environment that affect the dynamics of the observed process. Situation monitoring organizes the identification of such information through regular source tracking of heterogeneous (structured and unstructured) information and expert knowledge. It includes the detection and identification of events and system-forming factors that affect the dynamics of the observed process and the formation of signals about the state of the current situation. We call the factors system-forming, since in their unity they form a system that reflects a holistic view of the situation in the context of the problem being solved. The formation of signals is carried out on the basis of processing information about potentially significant events and factors by constructing scenarios for the development of the situation with an assessment of the significance of the effects of these events on the observed process.

Digital monitoring reveals structural shifts that occur when changing the dynamics of the series of individual quantitative indicators and / or changing the relationships between them: changes in trend, level, variance. The methods of digital monitoring used by us are based on algorithms of sequential analysis (Wald, 1947, Page, 1954) adapted for monitoring non-stationary processes (Grebenyuk, 2020).

Signals from situation and digital monitoring systems go to the supervisor for organizing information exchange between them and transmitting the generated signals to the system for solving target tasks related to the analysis of the influence of these events on the observed process and the prediction of its state.

In accordance with the purpose of the paper, the contribution of this research is as follows:

1. We proposed a monitoring organization model that includes, in addition to monitoring the time series describing the dynamics of the process, monitoring the situation in the macro and business environment, and a supervisor with the following functions: 1) – formation of input data for each type of monitoring; 2) implementation of information interaction between the two monitoring systems; 3) transfer of aggregated signals to the input of the tasks to be solved for the research and forecasting of the state of the process under study.

2. To implement situation monitoring, we have developed an algorithm for generating signals about the state of the external environment, formed as a result of analysing significant events and modelling the situation on the fuzzy cognitive map (FCM) (Dickerson and Kosko, 1994, Avdeeva, Kovriga and Makarenko, 2016). The FCM has found wide application in knowledge engineering for structuring and representing causal knowledge, which allows formalizing the knowledge domain in the form of domain-oriented concepts (factors) and relationships between them, especially when solving problems in situations of uncertainty (Cheah et al., 2008). In addition, FCM is a model for integrating private knowledge of diversified experts into a holistic generalized view of the situation, thereby increasing the validity of the conclusions (results) obtained on its basis. In this research, the FCM is a model of causal influences of system-forming factors that reflect the situation of interaction between the observed object and the external environment.

3. We have developed an algorithm for monitoring groups of time series, each of which describes distinct aspects of the development of the situation. The monitoring algorithm is an ensemble of sequential analysis algorithms configured to detect changes of the following type: trend change, variance change.

2 GENERAL DESCRIPTION OF THE MODEL FOR MONITORING OF SOCIO-ECONOMIC PROCESSES

Figure 1 shows the control scheme of the process of detection, identification and assessment of significant changes in the observed processes in situation and digital monitoring modes. Top of Figure 1 shows the process of forming and structuring the information necessary for the monitoring procedure.

To get a holistic view of the situation (interaction of the observed object with the external environment), we perform structuring and formalization of the subject area in the form of the FCM, in which we distribute system-forming factors into groups (SF-groups).

SF-groups characterize the belonging of system-forming factors to certain aspects of the situation. For example, for commodity markets these are market factors of the business environment related to supply and demand, financial and economic indicators of the external environment, factors of influence of state regulators, etc.

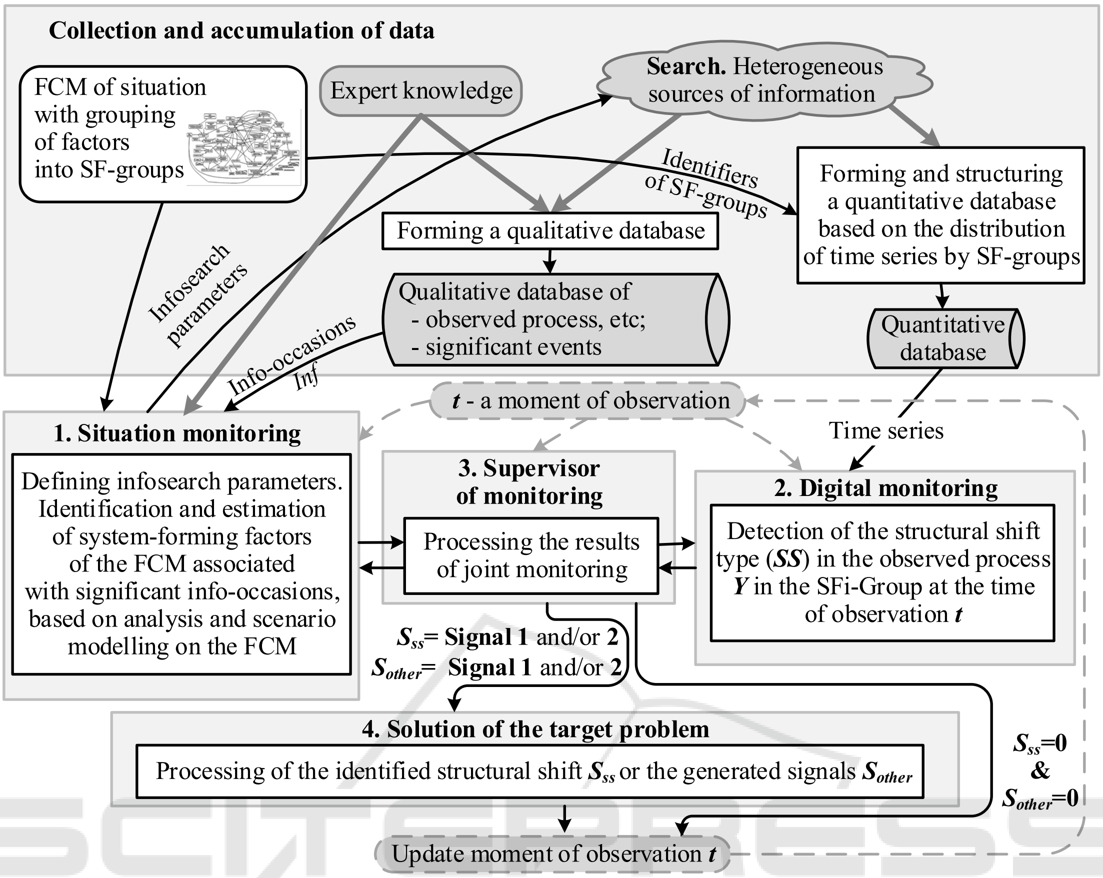

Figure 1: The control scheme of detection, identification and assessment of changes in the observed processes.

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We form the line-up of the databases based on the results of a survey of experts, analysis of diverse information sources, and recommendations from the FCM of the situation. The qualitative data base receives information about the structure of interactions between the observed process and related processes, about expertly significant events and factors that affect changes in these processes. The quantitative database includes time series of processes, distributed in SF-groups.

Monitoring realizes the following functions: detection of structural shifts – changes in the time series properties describing the process dynamics (Block 2 on Figure 1); detection and identification of changes in the state of macro- and business environment (Block 1 on Figure 1). The monitoring supervisor (Block 3) is intended for processing the results of joint monitoring, their confirmation and transfer of responses to the target problem solving block (evaluation of the current situation, identification of causal relationships between groups of parameters, forecasting on different time horizons, etc.) (Block 4).

We form assessments of the significance of the event consequences occurring in the external environment and signals of situation monitoring by using the following tools: (i) a model for representing causal influences between significant system-forming factors, reflecting the influence of the macro- and business environment on the observed process – the FCM of situation; (ii) author methods of structural analysis and modelling based on the FCM of situation

(Avdeeva, Kovriga and Makarenko, 2016, Avdeeva, Grebenyuk and Kovriga, 2020a).

Situation monitoring (Block 1) keeps track significant events that may influence the dynamics of processes for which a certain target task is being solved (forecasting the target indicator, analysing the dynamics of relationships, comparative analysis of SF-groups activity, etc.). Based on the results of the analysis of significant events Inf, Block 1 generates and transmits following signals to the supervisor: *Signal 1* – a reversal of target indicator change direction, *Signal 2* – significance weights of SF-groups, or 0 – no signal ($Signal_{other}$=*Signal 1* and\or *Signal 2* or 0. For each time series in which a change is detected, Block 2 generates, at the moment of detection, a signal *SS* of the following structure: {moment of detection *t*}, {time series name, name of the SF-group it belongs to} {type of change: level, trend, volatility} {parameter value after detected change} {list of series that are causal by Grainger for this series}. The signal from block 2 is transmitted to the supervisor input.

In block 1 of situation monitoring, if a potentially significant event *Inf* is detected, which can cause a structural shift *SS*, the corresponding signals S_{SS}= *Signal 1* and\or *Signal 2* are generated. The supervisor sends this information to block 4 to correct the algorithm of the target problem solution. If the event is not detected, then the supervisor sends the signal S_{SS}=0 to Block 4.

3 DIGITAL MONITORING

3.1 Monitoring Object and Basic Algorithm

The objects of digital monitoring considered here is the set of time series, distributed among groups of system-forming factors of the situation (SF-groups). These objects have the following features: (i) the series of observed indicators are non-stationary processes with a stochastic trend; (ii) time series belonging to the same SF-group follow general trends. Examples of such objects can serve as time series of commodity market prices subject to joint movement (Liu et al., 2022).

The constructed digital monitoring system consists of a set of sequential analysis algorithms (Page, 1954), which detect changes in the parameters of the observed time series distribution, provided that these values are accurately known before and after the change. To monitor each individual time series, we apply the algorithm proposed in (Nikiforov, 2000). The algorithm solves the following problem. Let $Y_t \in R, t = 1,2,...$ is an independent sequence of observations $F(X_t, \Theta_0)$ with parameter Θ_0, which after an unknown and non-random time moment $t > t_\alpha$ begins to change according to the distribution law $F(X_t, \Theta_m)$ with parameter Θ_m, m=1,2,…,r. It is required to detect as soon as possible the fact of change of parameter θ and determine the type of change m.

When next observation arrives, the algorithm calculates a pair (N, ν), where N is the point in time at which the algorithm signals the presence of changes, ν is the type of change. In (Nikiforov, 2002), it is proved that at exactly known parameters of signal distribution before and after changes the algorithm is optimal by criterion of minimum of maximum average delay of detection with restrictions on frequency of false alarms and probability of false diagnostics.

Since we do not know the exact values of the parameters after the change, we determine the range of values of the monitored parameters according to historical data: no changes, small changes, medium, large. For each area and for each type of shift, we assign the values of the parameter Θ_m, which are different for different time series.

3.2 Algorithms for Monitoring Non-Stationary Processes

The algorithm (Nikiforov, 2000) accepts a random independent digital sequence as input, and the observed object is a non-stationary series Y_t integrated of the first order, so the problem arises of generating signals supplied to the input of the basic algorithm. To detect changes in non-stationary series, we build an autoregression model based on the differences $\Delta Y_t = Y_t - Y_{t-1}$ in an interval without structural shifts:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \beta_i \Delta Y_{t-i} + \nu_t, \tag{1}$$

where $\beta_i (i = 1,...,k-1)$ are the coefficients of the model; μ is drift; $\nu_t \sim N(0,\sigma^2)$ is a random sequence. We calculate its residuals, which we send to input on the algorithm for detection changes

$$\mathrm{Re}\, s_t = \Delta Y_t - \tilde{\mu} - \sum_{i=1}^{k-1} \tilde{\beta}_i \Delta Y_{t-i}. \tag{2}$$

The algorithm for detecting structural shifts of a non-stationary series is proposed in [7] and includes 2 algorithms for detecting changes in drift and variance along the vector of residuals (Eq. 2) of the model (Eq. 1). When receiving a request from the situation monitoring unit, the algorithm narrows the range of permissible changes in tuning parameters in order to increase the probability of detection due to some increase in false alarms.

4 SITUATION MONITORING

The purpose of situation monitoring (Block 1 in Figure 1) is (i) tracking environment events that affect the dynamics of the observed process Y , which cannot be identified by digital monitoring in quantitative data (time series) at the time of observation; (ii) the identification, assessment of the significance of these events for changing Y and the formation of appropriate signals for changing settings or/and expanding the composition of objects of observation in Block 2 of digital monitoring.

The basis for tracking and filtering information is the FCM of the situation, which reflects the causal influences between significant system-forming factors that characterize the interaction of observed process and the processes of the macro- and business environment. The FCM with the distribution of factors by SF-groups structures the knowledge subject domain, which allows you to organize a directed search for information in heterogeneous sources.

The detected potentially significant info-occasion *Inf* is associated with the system-forming factors $\{\tilde{x}^{\mathrm{inf}}\}$ corresponding to it and evaluated on the basis of modelling on the FCM S^{inf} scenario of the development of the situation "what will happen if", the output of which is the value of factor $\tilde{y}$, characterizing the qualitative dynamics of the observed process Y and allowing us to assess whether Inf affects the change in Y. We evaluate the modelling results of the scenario S^{inf} on the basis of the developed estimates characterizing the significance of the factor influence and their activity on the object Y dynamics of the digital monitoring (Avdeeva, Grebenyuk and Kovriga, 2020b). We calculate these estimates by the values of the integral influences between any factors of FCM. Each such integral assessment takes into account all direct and indirect influences between a pair of factors in the FCM of situation. According to the results of the scenario S^{inf} evaluation, which reflects the influence of the event *Inf* on the dynamics of Y, we form signals S=*Signal 1* and\or S=*Signal 2* or S=0 (no signal). *Signal 1* indicates a reversal of change direction of indicator $\tilde{y}$ due to event *Inf*. *Signal 2* transmits the significance weights (influence) of SF-groups on Y whose system-forming factors were included in the scenario S^{inf}. These weights characterize the contribution of each SF-group to the change in Y, taking into account the significance of the influence of active factors $\{\tilde{x}^{\mathrm{inf}}\}$ belonging to these groups on Y and the degree of activity of manifestation of these factors in the scenario S^{inf}. The signal $S = 0$ indicates the absence of significant events affecting Y at the time of observation t.

After processing, the supervisor (Block 3) sends situation monitoring signals to Block 2 of digital monitoring and to the target problem solving block (Block 4) (Figure 1).

5 CONCLUSIONS

In modern conditions of instability of the environment, the uncertainty of its impact on changing the processes of functioning social, economic and financial systems, the role of monitoring the processes, the dynamics of which is affected by the state of the external environment, is increasing. In such systems, in addition to the traditional monitoring of digital indicators, situation monitoring based on the processing of expert information is a necessary component of supporting the solution of the target tasks of the analysis of dynamic systems at different time horizons.

This paper presents a model of joint application of situation and digital monitoring, which expands the possibilities of digital monitoring by providing additional information to it. The joint monitoring algorithm includes: 1) digital monitoring algorithms to detect structural shifts that use signals from situation monitoring, in addition to observations of digital indicators; 2) situation monitoring of observed processes in interaction with the external environment, conducted on the basis of processing expert knowledge, tracing information from heterogeneous sources about potentially significant events of the external environment, scenario analysis and modelling of the situation in order to assess the expected consequences of these events (the occurrence of structural shifts) on the dynamics of the observed process.

We tested the efficiency of the proposed procedure on the example of commodity market monitoring using (1) information about environmental events and significant factors affecting prices, (2) time series of macroeconomic indicators, prices for metal products and raw materials. We carried out the monitoring as part of solving the problem of correction on the forecasting horizon of the constructed monthly forecast of prices for ferrous scrap for 2019 (Avdeeva, Grebenyuk and Kovriga (2021)). The experiment showed that the forecast error is reduced by several times (in comparison with the "naive" forecast) due to the structuring of the situation, the formation of forecasts using ensembles of models, the correction of the situation on the forecast horizon based on the results of situational monitoring and digital monitoring. The experiment confirms that joint monitoring improves the quality of detection of structural shifts by digital monitoring due to the information provided by situational monitoring, helps to identify the causes of their occurrence and take this information into account when forming a forecast in order to improve its accuracy.

The practical significance of the proposed monitoring procedure consists in increasing the efficiency of structural shift detection algorithms by obtaining additional information by them, and, accordingly, in enhancing the capabilities of expert-analysts and forecasters in solving the target problems of analysis and forecasting in situations of uncertainty and instability based on the processing of heterogeneous information.

ACKNOWLEDGEMENTS

The results presented in the paper is partitionally supported by grant of RSF № 23-21-00455, https://rscf.ru/en/project/23-21-00455/.

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