**Information systems. Computer sciences. Issues of information security**

**Информационные системы. Информатика. Проблемы информационной безопасности**

*UDC 004.021:65.012.26*
*https://doi.org/10.32362/2500-316X-2026-14-2-7-16*
*EDN VCTFHE*

RESEARCH ARTICLE

# Clustering of multidimensional temporal data as part of information support for management decisions

**Mikhail A. Anfyorov** @

*MIREA – Russian Technological University, Moscow, 119454 Russia*
@ *Corresponding author, e-mail: anfyorov@inbox.ru*

• **Submitted:** 02.02.2025 • **Revised:** 20.11.2025 • **Accepted:** 09.02.2026

**Abstract**
**Objectives.** The aim of information support for management decision-making is to find the most optimal option. Cluster analysis of multivariate data characterizing socioeconomic systems is widely used. In this work, the author aims to increase the efficiency of decisions made to manage these systems based on the clustering of temporal multidimensional data.
**Methods.** The methods of cluster analysis were used, as well as the provisions of the theory of systems and mathematical statistics.
**Results.** A methodology for analyzing the functioning of socioeconomic systems was developed. The analysis is implemented in three stages. Firstly, clustering over the values of feature variances was applied. Secondly, the distance of clustering objects from the center of their cluster and their dispersion was calculated at the points of time coordinates. Thirdly, the change in belonging to a certain cluster of objects that came into view earlier was monitored. Unstable systems were then identified.
**Conclusions.** Two cases were considered to justify the effectiveness of the methodology developed herein. First, using the example of the tax administration, the detection of deliberate distortion of information was considered. Secondly, identifying the abnormal functioning of the regions of the Russian Federation using the example of decision-making in the framework of socioeconomic development management was considered. The analysis demonstrated good results and we can thus recommend the proposed methodology for practical use in information systems for supporting management decisions.

**Keywords:** information support, decision-making, cluster analysis, multivariate time data

**For citation:** Anfyorov M.A. Clustering of multidimensional temporal data as part of information support for management decisions. *Russian Technological Journal.* 2026;14(2):7–16. https://doi.org/10.32362/2500-316X-2026-14-2-7-16, https://www.elibrary.ru/VCTFHE

**Financial disclosure:** The author has no financial or proprietary interest in any material or method mentioned.

The author declares no conflicts of interest.

НАУЧНАЯ СТАТЬЯ

# Кластеризация многомерных временных данных в рамках информационной поддержки принимаемых управленческих решений

**М.А. Анфёров** @

*МИРЭА – Российский технологический университет, Москва, 119454 Россия*
*@ Автор для переписки, e-mail: anfyorov@inbox.ru*

• **Поступила:** 02.02.2025 • **Доработана:** 20.11.2025 • **Принята к опубликованию:** 09.02.2026

**Резюме**
**Цели.** Информационная поддержка принятия управленческих решений в различных предметных областях направлена на поиск оптимального варианта из множества альтернативных. Что касается принимаемых решений в части функционирования социально-экономических систем, то здесь широко используется кластерный анализ на многомерных данных, характеризующих эти системы, Цель работы – синтез и исследование методики анализа функционирования социально-экономических систем, построенного на кластеризации характеризующих их временных многомерных данных, с целью повышения эффективности принимаемых решений в управлении такими системами.
**Методы.** Использованы методы кластерного анализа, а также положения теории систем и математической статистики.
**Результаты.** Разработана методика анализа функционирования социально-экономических систем, использующая кластеризацию ее структурных элементов в пространстве временных многомерных данных. Анализ реализуется в три этапа. Во-первых, производится замена значений признаков на значения их дисперсий в рамках исследуемого временного интервала. Кластеризация с учетом новых значений признаков позволяет выявить объекты кластеризации с высокой неустойчивостью значений признаков во времени. Во-вторых, реализуется кластеризация во всех дискретных точках временной координаты с дальнейшим расчетом удаленностей объектов до центра своего кластера и их дисперсии. Анализ этих дисперсий также позволяет выявить объекты с высокой неустойчивостью данных. В-третьих, отслеживается изменение принадлежности определенному кластеру объектов, попавших ранее в поле зрения. Выявленные неустойчивости в данных позволяют косвенно судить о нестабильном функционировании анализируемой системы или умышленном искажении представленной информации.
**Выводы.** В рамках обоснования эффективности разработанной методики рассмотрено два случая: выявление умышленного искажения информации на примере налогового администрирования и случай выявления аномального функционирования регионов Российской Федерации на примере принятия решений в рамках управления их социально-экономическим развитием. Поведенный анализ показал хорошие результаты и позволяет рекомендовать предлагаемую методику к практическому использованию в информационных системах поддержки управленческих решений.

**Ключевые слова:** информационная поддержка, принятие решений, кластерный анализ, многомерные временные данные

**Для цитирования:** Анфёров М.А. Кластеризация многомерных временных данных в рамках информационной поддержки принимаемых управленческих решений. *Russian Technological Journal*. 2026;14(2):7–16. https://doi.org/10.32362/2500-316X-2026-14-2-7-16, https://www.elibrary.ru/VCTFHE

**Прозрачность финансовой деятельности:** Автор не имеет финансовой заинтересованности в представленных материалах или методах.

Автор заявляет об отсутствии конфликта интересов.

## INTRODUCTION

Cluster analysis [1], as an effective mechanism of intelligent information technologies, is used in resolving a wide range of tasks related to decision-making in various subject areas. In the public administration, for example, it can be applied in developing socioeconomic policy at the regional level [2, 3], in tax regulation [4, 5], in the fields of education [6] and medicine [7, 8], computer science [9, 10] and information security [11], and in the field of mechanical engineering [12, 13]. A wide range of studies have addressed management processes in the economic sphere when solving decision-making problems. Examples of these are investment processes [14], assessing the financial stability of information technology (IT) companies [15], and others. In addition to management decision-making, cluster analysis is also used to support project decision-making [16, 17].

However, all of the examples given above apply static (spatial) data obtained at a specific point in time. On the other hand, analysis which takes into account the dynamics of the properties of objects reflected in the data enables the capabilities of cluster analysis to be expanded in support of management decision-making.

It is worth noting the research being implemented in this area. Firstly, there have been studies of the clustering of one-dimensional [18, 19] and multidimensional [20] time series which increases the efficiency of clustering, but not decision-making. The same goal is being pursued by the transition from the time domain of data to a two-dimensional discrete function [21] using continuous wavelet transformation [22]. The inclusion of the time parameter in the feature space during clustering [23] enables the dynamics of the state of the analyzed objects to be expressed. The clustering of objects as dynamic systems has also been studied in [24, 25].

More in-depth analytics are based on identifying patterns in the dynamics of clustered objects through the dynamics of time series data. Thus, the expansion of analytics is based on an approach which involves clustering objects based on the proximity of the dynamics of time series of a set of indicators characterizing them [26]. In this case, a range of metrics and methods for assessing such proximity are analyzed and compared, including the dynamic time warping (DTW) algorithm [27]. The study of the dynamics of cluster structures in network models of stock markets has made it possible to identify an indicator of an impending crisis in the form of an increase in the stability of these structures [28].

In this study, information support for management decisions is based on an analysis of the hidden influence of factors on the behavior (function) of the system (Fig. 1). If the explicit influence directly determines the decision being made, then the hidden influence requires identification using modern analytical tools and information technologies, as well as an adequate interpretation of the results obtained.

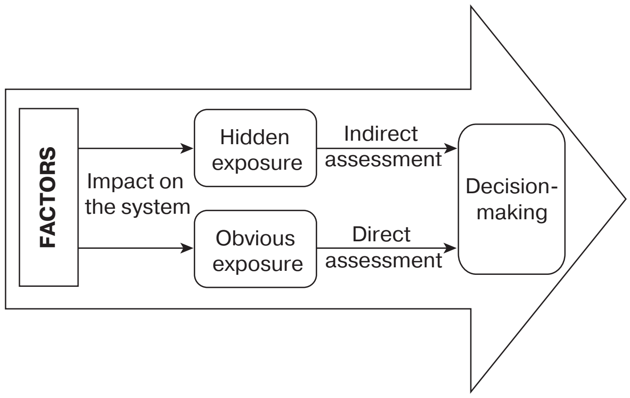


**Fig. 1.** Consideration of the impact of factors on the system when making decisions

At the same time, the hidden impact of factors on the system being analyzed is revealed through the variable behavior of the objects under study in relation to the clusters being formed. This variability may signal either deliberate distortion of the data provided (e.g., in tax returns) or unstable functioning of the system requiring managerial intervention.

## METHODOLOGY

The temporal data analysis used is based on their clustering using the self-organizing map (SOM) method [29]. This is within the framework of the previously proposed approach and covers various levels of depth of research into system behavior [30]. Kohonen SOM enable the qualitative component of the analysis to be enhanced by visualizing the clusters formed using map data. In the proposed methodology, three data analysis tools are implemented to improve the adequacy of the decision made.

The first tool is a filter to limit the power of the analyzed set of features $\mathbf{p}_k^t = (p_{k1}^t, p_{k2}^t, \dots, p_{kn}^t)$, which depend discretely on the time parameter $t$ ($k$ is the number of objects in the clustered set, $m$ is the number of features). The values of the features are replaced with the values of their dispersions within the time interval under study ($w$ is the number of fixed time coordinates):

$$D_{kj} = \frac{1}{w-1}\sum_{i=1}^{w}(p_{kj}^i - \overline{p}_{kj})^2, \; \overline{p}_{kj} = \frac{1}{w}\sum_{i=1}^{w} p_{kj}^i. \quad (1)$$

Further, clustering is performed in the space of new features with the identification of objects belonging to clusters with high dispersion values associated with high instability of the values of the analyzed features. The objects identified are recorded for further analysis as systems with unstable time data. Objects with a high feature dispersion possibly caused by a trend in their values, characterizing a positive or negative trend, may also be noted. Additional regression analysis is required for clarification (see example below).

The second analysis tool is designed to identify instability in the images of the clustered objects within clusters and involves a series of steps.

In the first stage, clustering is implemented at all discrete points of the time coordinate ($r$ is the number of the time coordinate). Next, the distance $d_k^r$ of the $k$th object to the center of its cluster is calculated.

In the second stage, at each moment in time $r$, the variance of the values found in the first stage is calculated as $d_k^r$ in the interval covering the current and previous time coordinates:

$$D_k^r = \frac{1}{r-1}\sum_{t=1}^{r}(d_k^t - \bar{d}_k^r)^2, \ \ \bar{d}_k^r = \frac{1}{r}\sum_{t=1}^{r} d_k^t, \ \ r = \overline{2, w}. \quad (2)$$

In the third stage, the temporal dependencies of the dispersions (2) are displayed in the form of a diagram which includes all clustered objects. The diagram enables objects with unstable temporal data to be identified at a new level.

The application of the third tool involves tracking possible changes in the affiliation of a specific cluster of objects previously in the field of view (Fig. 2). Such changes allow us to indirectly assess (Fig. 1) the unstable functioning of the system or deliberate distortion of information. They also allow us to refine previously obtained conclusions about objects which have fallen into the risk group. For this purpose, diagrams are the best way to express these objects.

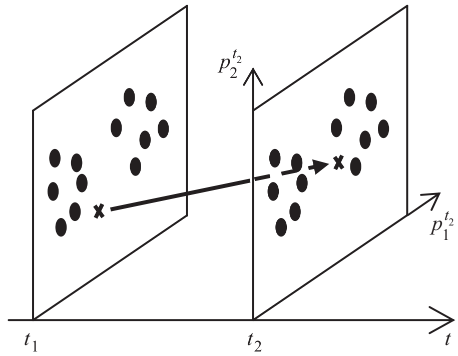


**Fig. 2.** Clustering results dynamics

The second and the third tools can be applied in different sequences, as well as in parallel.

The interrelationship between the stages implemented within the analysis methodology is presented in a block diagram of the corresponding algorithm (Fig. 3).

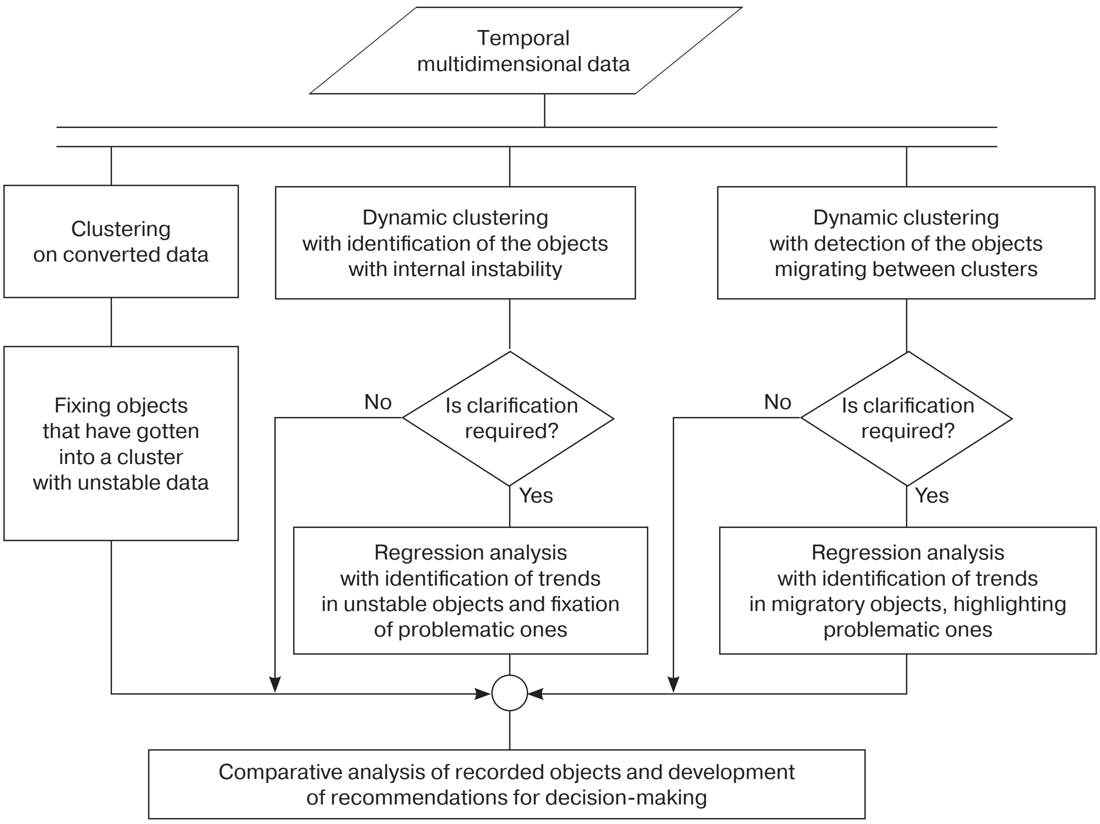


**Fig. 3.** Method implementation algorithm

## DETECTION OF INTENTIONAL DISTORTION OF INFORMATION

The application of the proposed analysis in identifying the deliberate distortion of information is demonstrated using the example of tax administration. Here decisions need to be made about planning field tax audits at taxpayer enterprises. It is initially assumed that the aforementioned distortion allows with a certain degree of probability (Fig. 1) the dishonesty of the management of such enterprises to be assessed. The selection of parameters (features) for clustering was based on a number of preferences:

- availability of their calculation in financial statements;
- their correlation with bankruptcy risk (indicators are reflected in the relevant methodology of the Federal Insolvency Service under the State Committee of the Russian Federation for State Property Management);
- inclusion in Altman's model [31].

As a result, sixteen financial indicators were selected for the twenty companies analyzed. They enabled an assessment of their solvency to be made as well as the financial stability of their economic systems, the profitability of their production, and their business activity in terms of inventory turnover and accounts receivable and payable. The dynamics of these indicators were tracked over a period of eight quarters.

Clustering in the space of new features (1), according to the proposed methodology, allowed for enterprises with high instability of initial data values to be identified (enterprises with conditional numbers 4 and 12). According to the clustering results, they were isolated in their clusters.

The analysis of intra-cluster instability based on the value of the variances (2) resulted in the construction of a diagram (Fig. 4). The pattern of the graphs in the diagram identified critical enterprises with data instability, leading to abnormal behavior of the graphs corresponding to these enterprises. At this stage, the group of enterprises under review included the previously noted enterprises 4 and 12, as well as enterprises 2 and 13.

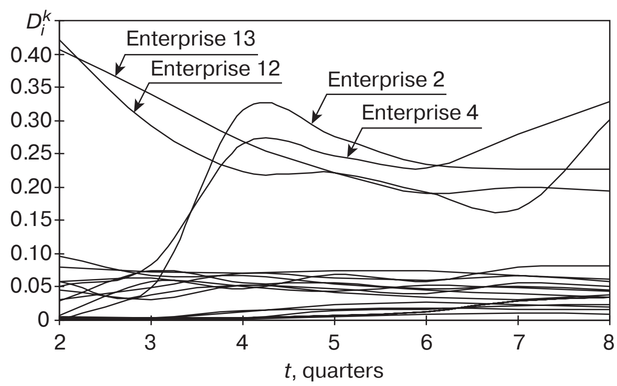


**Fig. 4.** Dispersion dynamics (2) in enterprise analysis

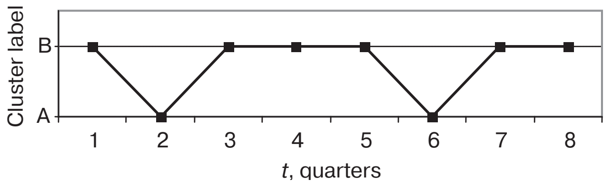


**Fig. 5.** Migration of enterprise 4 between clusters

Migrations between clusters (the third tool of the analysis methodology) were found to affect enterprises 2, 4, and 12, as already been noted in previous stages of the analysis. A graphical illustration for enterprise 4 is shown in Fig. 5.

Thus, based on the results of the analysis, field tax audits were recommended for enterprises 2, 4, and 12, and, if possible, for enterprise 13.

## IDENTIFYING SYSTEM FUNCTIONING INSTABILITY

The application of the proposed analysis in identifying abnormal systems functioning can be demonstrated using the example of decision-making in the context of socioeconomic development management of the regions in the Russian Federation. The analysis used key indicators characterizing the state of the regional socioeconomic system[1] for the period from 2014 to 2020 (a period of steady progressive development). The volume indicators were converted to relative values by dividing them by the number of employed people in the region. The Republic of Crimea and the city of Sevastopol were excluded from the analysis, since during this transitional period their socioeconomic systems were on the path to stabilization. Moscow, the Moscow oblast, and St. Petersburg, as well as regional structures which are part of regions (e.g., the Yamalo-Nenets Autonomous Okrug within the Tyumen oblast), were not considered.

Unlike the case discussed above, where deliberate data distortion was identified during dynamic cluster analysis of system functioning, dispersion estimates must take into account the possible trend of the relevant indicators (system characteristics) which cause high dispersion values.

In the example under consideration, when clustering in the space of feature variances (1), region 69 (Tver oblast) fell into the cluster of system

[1] *Rossiya v tsifrakh: kratkii statisticheskii sbornik* (*Russia in numbers: a short statistical collection*). Moscow: Rosstat; 2020, 550 p. (In Russ.). ISBN 978-5-89476-488-7

instability (high variance values). In order to identify the presence of a trend, a regression analysis was performed to identify the empirical dependence on time of the indicator $v = v(t)$, as determined by the ratio of the gross regional product (billion rubles) to the average annual number of employed population (thousand people) (Fig. 6). The high value of the coefficient of determination $R^2$ indicates a stable positive trend for this characteristic. This allows us to exclude this region from the cluster of unstable regions. As for other indicators, checking for trends in this region yielded positive results. Thus, for the relative volume of goods shipped from own manufacturing, a stable trend $s = s(t)$ with a coefficient of determination $R^2 = 0.77$ was confirmed.

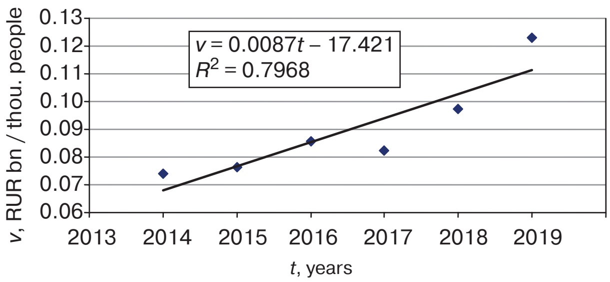


**Fig. 6.** Trend of indicator *v* for region 69

In the case of a specific clustering object, there may be cases where some indicators have a stable trend, while others have a stochastic spread of values. In this case, a heuristic assessment will be required to make a decision.

Other regions classified as unstable (46 in Kursk oblast, 23 in Krasnoyarsk krai, 51 in Murmansk oblast, and 76 in Yaroslavl oblast) are characterized by a high level of stochasticity, making them candidates for increased attention in terms of state socioeconomic regulation.

The diagram illustrating intracluster instability by dispersion (2) (Fig. 7) showed abnormal behavior of the graphs for the regions already mentioned above. Regions 2 (Republic of Bashkortostan) and 11 (Republic of Komi) were added.

At the stage of identifying migration between clusters (Fig. 8), regions 65 (Sakhalin oblast) and 68 (Tambov oblast) were included in the analysis.

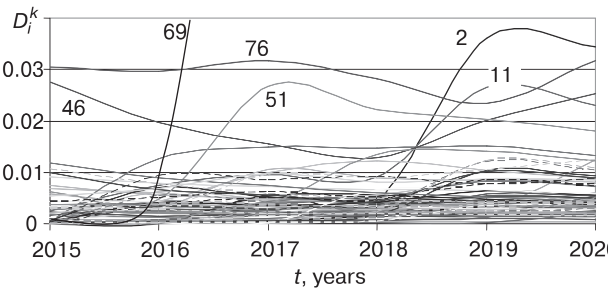


**Fig. 7.** Dynamics of dispersions (2) in regional analysis

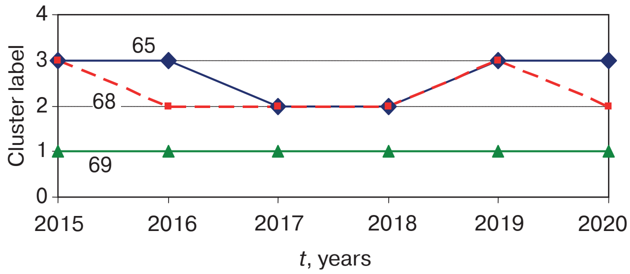


**Fig. 8.** Migration of regions 65, 68, and 69 between clusters

The absence of migration between clusters in region 69 once again confirmed its high level of socioeconomic development.

Regression analysis of the regions added showed that the increase in dispersion (2) for regions 2 and 11 can be largely explained by the positive dynamics of their indicators (see the example for region 2 in Fig. 9 with an acceptable $R^2$ value). In the case of regions 65 and 68, their migration between clusters is determined by the high level of stochasticity of economic indicators (see the example for region 65 in Fig. 9 with a low $R^2$ value), requiring measures to be taken within the framework of state regulation.

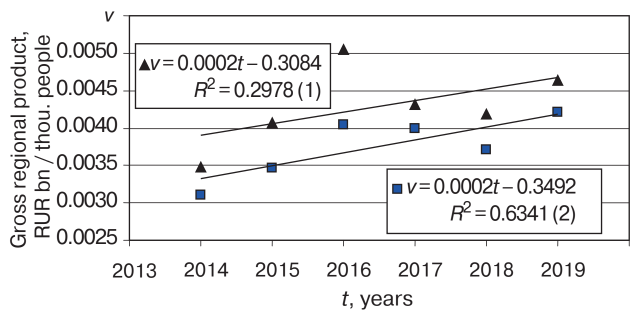


**Fig. 9.** Trends in relative gross regional product: (1) for region 65 (black triangles); (2) for region 2 (blue squares)

Thus, based on the results of the analysis, recommendations can be given on the development of measures within the framework of state regulation, aimed at improving and stabilizing the functioning of the socioeconomic system in regions 46, 23, 51, 76, 65, and 68.

## CONCLUSIONS

The article presents an approach to information support for management decisions in conditions of uncertainty. This is achieved by means of an indirect assessment of the impact of factors on the controlled system using a method based on cluster analysis of time series data. The proposed technology is focused on two classes of tasks: decision-making in conditions of possible deliberate data distortion; and when detecting unstable functioning of the system being analyzed.

The proposed theoretical provisions have been tested in practice using real data to resolve matters of concern to the tax administration and state regulation of the functioning of regional socioeconomic systems.

## REFERENCES

1. Anfyorov M.A. Genetic clustering algorithm. *Russian Technological Journal*. 2019;7(6):134–150 (in Russ.). https://doi.org/10.32362/2500-316X-2019-7-6-134-150
2. Zamyatina E.E. Clustering of constituent entities of the Russian Federation by the level of development of creative industries. *Progressivnaya ehkonomika* = *Progressive Economy*. 2024;9:113–128 (in Russ.). https://doi.org/10.54861/27131211_2024_9_113
3. Protasov Yu.M., Yurov V.M. Clusterization of the Regions of the Russian Federation by their Level Socio-Economic Development. *Vestnik Moskovskogo gosudarstvennogo oblastnogo universiteta. Seriya Ehkonomika = Bulletin of Moscow Region State University. Series*: *Economicsi*. 2022;2:95–103 (in Russ.). https://doi.org/10.18384/2310-6646-2022-2-95-103
4. Anfyorov M.A., Rashitova O.B. SADT modeling of the taxation system in the Russian Federation. *Ehkonomika i upravlenie*: *nauchno-prakticheskii zhurnal = Economics and Management*: *Research and Practice Journal.* 2015;124(2):94–101 (in Russ.). https://www.elibrary.ru/tqjqfj
5. Vylkova E.S., Viktorova N.G., Naumov V.N., Pokrovskaya N.V. Tax clusterization of regions of the Russian Federation to identify territories-drivers of sustainable development. *Vestnik Tomskogo gosudarstvennogo universiteta. Ehkonomika = Tomsk State University Journal of Economics.* 2021;53:138–157 (in Russ.). https://doi.org/10.17223/19988648/53/11
6. Greenberg G.M., Nikolaeva Y.S., Hegay L.B. Cluster approach to development of electronic educational resources for students of the technical university. In: *Reshetnev Readings*: *Proceedings of the 25th International Scientific and Practical Conference.* Krasnoyarsk, November 10–12, 2021. Krasnoyarsk: Siberian State University of Science and Technology; 2021. P. 685–687 (in Russ.). https://elibrary.ru/yjchna
7. Nosova S.A., Turlapov V.E. Detection of brain cells in optical microscopy based on textural features with machine learning methods. *Program. Comput. Soft.* 2019;45(4):171–179. https://doi.org/10.1134/S0361768819040054
[Original Russian Text: Nosova S.A., Turlapov V.E. Detection of brain cells in optical microscopy based on textural features with machine learning methods. *Programmirovanie*. 2019;4:36–45 (in Russ.). https://doi.org/10.1134/S0132347419040058 ]
8. Hamad Y.A., Zotin A.G., Simonov K.V., Medievsky A.V., Chizhova I.G. Detection and evaluation of breast pathology based on fuzzy clustering and discrete wavelet transform. *Meditsina i vysokie tekhnologii = Medicine and High Technology*. 2023;2:5–13 (in Russ.). https://www.elibrary.ru/ujqlwd
9. Raja R., Ganeshkumar P. QOSTRP: a trusted clustering based routing protocol for mobile ad-hoc networks. *Program. Comput. Soft.* 2018;44(6):407–416. https://doi.org/10.1134/S0361768818060099
[Original Russian Text: Raja R., Ganeshkumar P. QOSTRP: a trusted clustering based routing protocol for mobile ad-hoc networks. *Programmirovanie.* 2018;6:28–41 (in Russ.). https://doi.org/10.31857/S013234740002763-4 ]
10. Kasimov D.R., Kuchuganov A.V., Kuchuganov V.N., Oskolkov P.P. Approximation of color images based on the clusterization of the color palette and smoothing boundaries by splines and arcs. *Program. Comput. Soft.* 2018;44(5):295–302. https://doi.org/10.1134/S0361768818050043
[Original Russian Text: Kasimov D.R., Kuchuganov A.V., Kuchuganov V.N., Oskolkov P.P. Approximation of color images based on the clusterization of the color palette and smoothing boundaries by splines and arcs. *Programmirovanie.* 2018;5:3–11 (in Russ.). https://doi.org/10.31857/S013234740001211-7 ]
11. Bereshpolov I.S., Kravchenko Yu.A., Sleptsov A.G. Data clustering algorithm for protecting confidential information on the internet. *Izvestiya YuFU. Tekhnicheskie nauki = Izvestiya SFedU. Engineering Sciences.* 2023;3(233):74–85 (in Russ.). https://doi.org/10.18522/2311-3103-2023-3-74-85
12. Kharakhinov V.A., Sosinskaya S.S. The visualization methods for cluster analysis results of mechanical engineering components based on neural network. *Programmnaya inzheneriya = Software Engineering*. 2017;8(4):170–176 (in Russ.). https://doi.org/10.17587/prin.8.170-176
13. Kuchuganov V.N., Kuchuganov A.V., Kasimov D.R. Clustering algorithm for a set of machine parts on the basis of engineering drawings. *Program. Comput. Soft.* 2020;46(1):25–34. https://doi.org/10.1134/S0361768820010041
[Original Russian Text: Kuchuganov V.N., Kuchuganov A.V., Kasimov D.R. Clustering algorithm for a set of machine parts on the basis of engineering drawings. *Programmirovanie*. 2020;46(1):29–38 (in Russ.). https://doi.org/10.31857/S0132347420010045
14. Matveeva I.Yu. Clustering of retail investors and portfolio structure by asset class. *Izvestiya Sankt-Peterburgskogo gosudarstvennogo ekonomicheskogo universiteta*. 2023;4(142):180–184 (in Russ.). https://www.elibrary.ru/fnmsql
15. Batrasova A.D., Konovalova T.V., Komarov P.I. Clustering as a method of studying the financial stability of IT companies. *Upravlencheskii uchet = Management Accounting.* 2022;(1-2):177–182 (in Russ.). https://www.elibrary.ru/xaufce

16. Anfyorov M.A. Formalization of the structural solutions search for CAD/CAM System. In: *Computer Science*: *Problems, Methods, Technologies*: *Proceedings of the 22nd International Scientific and Practical Conference.* Voronezh, Voronezh State University, February 10–12, 2022. Voronezh: VELBORN; 2022. P. 881–886 (in Russ.). https://elibrary.ru/dsdxhp
17. Yakovlev D.D., Petrov D.Yu. Application of exploratory data analysis for clusterization of robotic assembly complexes structures. *Avtomatizirovannoe proektirovanie v mashinostroenii.* 2024;17:71–75 (in Russ.). https://doi.org/10.26160/2309-8864-2024-17-71-75
18. Stepanov M.A. Method to identify structural transformations of time series using fuzzy clustering principles. *Vestnik Ryazanskogo gosudarstvennogo radiotekhnicheskogo universiteta = Vestnik of Ryazan state Radioengineering University*. 2019;69:149–159 (in Russ.). https://doi.org/10.21667/1995-4565-2019-69-149-159
19. Kladov D.E., Berikov V.B., Klimontov V.V. Time Series Clustering Algorithm and Its Application for Glycemic Curve Analysis. In: *KNOWLEDGE – ONTOLOGY – THEORY: Proceedings of the 9th International Conference.* Novosibirsk, October 2–6, 2023. Novosibirsk: Sobolev Institute of Mathematics, SB RAS; 2023. P. 154–161 (in Russ.). https://elibrary.ru/qqzzvw
20. Tishhenko A.K., Pliss I.P. Segmentation of Multidimensional Nonstationary Time Series Using the Fuzzy Clustering Method. *Vostochno-Evropeiskii Zhurnal Peredovykh Tekhnologii.* 2012;4(58):24–26 (in Russ.). Available from URL: https://cyberleninka.ru/article/n/segmentatsiya-mnogomernyh-nestatsionarnyh-vremennyh-ryadov-s-pomoschyu-metoda-nechetkoy-klasterizatsii. Accessed February 02, 2025.
21. Dulya I.S. Applying deep learning techniques to the time series clustering problem. *Alleya nauki*. 2021;1(5):974–978 (in Russ.). https://elibrary.ru/nokchy
22. Hurley C., Mclean J. *Wavelet Analysis and Methods.* Waltham Abbey: ED-Tech Press; 2021, 366 p.
23. Spirina P.V., Semenova A.R. Cluster analysis of the dynamics of innovation activities of the constituent entities of the Russian Federation. *Ehkonomicheskie issledovaniya i razrabotki = Economic Development Research Journal*. 2021;8:42–53 (in Russ.). https://elibrary.ru/oiqybo
24. Zhikhalkina N.F. Dynamic approach to clustering problem. *Matematicheskie struktury i modelirovanie = Mathematical Structures and Modeling.* 2000;5:133–139 (in Russ.). Available from URL: https://cyberleninka.ru/article/n/dinamicheskiy-podhod-k-zadache-klasterizatsii. Accessed February 02, 2025.
25. Ryzhkov D.V. About Dynamic Time Series Clustering Methods. In: *Science. Technologies. Innovations*: *Collection of Scientific Papers of the 17th All-Russian Scientific Conference of Young Scientists.* Novosibirsk, December 04–08, 2023. Novosibirsk: NSTU; 2024. P. 178–182 (in Russ.). https://elibrary.ru/xykvdt
26. Zaitsev R.D. Study of the Effectiveness of Multivariate Clustering of Time Series for the Analysis of the Dynamics of Scientific and Technological Development. *Perspektivy razvitiya informatsionnykh tekhnologii.* 2015;25:7–13 (in Russ.). https://www.elibrary.ru/uhrwjt
27. Ten Holt G.A., Reinders M.J.T., Hendriks E.A. Multi-dimensional dynamic time warping for gesture recognition. In: *Thirteenth Annual Conference on the Advanced School for Computing and Imaging.* Netherlands: V. 300. 2007, 8 p. Available from URL: https://www.researchgate.net/publication/228740947. Accessed February 02, 2025.
28. Kocheturov A.A., Batsyn M.V., Pardalos P.M. Dynamics of cluster structures in stock market networks. *Zhurnal novoi ehkonomicheskoi assotsiatsii = The Journal of the New Economic Association.* 2015;4(28):12–30 (in Russ.). https://www.elibrary.ru/vdzrqh
29. Kohonen T. *Self-Organizing Maps.* 3rd ed. Berlin – New York: Springer-Verlag; 2001, 521 p.
30. Anfyorov M.A. Clustering in decision-making. *Informatsionnye tekhnologii. Problemy i resheniya.* 2020;2(11):97–102 (in Russ.). https://www.elibrary.ru/rwddvo
31. Davydova G.V., Belikov A.Yu. Methodology for Quantitative Assessment of Enterprise Bankruptcy Risk. *Upravlenie riskom.* 1999;3:13–20 (in Russ.). https://www.elibrary.ru/tdgdrb

## СПИСОК ЛИТЕРАТУРЫ

1. Анфёров М.А. Генетический алгоритм кластеризации. *Russian Technological Journal*. 2019;7(6):134–150. https://doi.org/10.32362/2500-316X-2019-7-6-134-150
2. Замятина Е.Э. Кластеризация субъектов Российской Федерации по уровню развития креативных индустрий. *Прогрессивная экономика*. 2024;9:113–128. https://doi.org/10.54861/27131211_2024_9_113
3. Протасов Ю.М., Юров В.М. Кластеризация регионов РФ по уровню их социально-экономического развития. *Вестник Московского государственного областного университета. Серия Экономика*. 2022;2:95–103. https://doi.org/10.18384/2310-6646-2022-2-95-103
4. Анфёров М.А., Рашитова О.Б. SADT-моделирование системы налогообложения в Российской Федерации. *Экономика и управление*: *научно-практический журнал*. 2015;124(2):94–101. https://www.elibrary.ru/tqjqfj
5. Вылкова Е.С., Викторова Н.Г., Наумов В.Н., Покровская Н.В. Кластерный анализ регионов РФ для выявления территорий – драйверов устойчивого развития: налоговая компонента. *Вестник Томского государственного университета. Экономика.* 2021;53:138–157. https://doi.org/10.17223/19988648/53/11
6. Гринберг Г.М., Николаева Ю.С., Хегай Л.Б. Кластерный подход к разработке электронных образовательных ресурсов для студентов технического университета. В сб.: *Решетневские чтения*: *Материалы XXV Международной научно-практической конференции.* Красноярск, 10–12 ноября 2021 г. Красноярск: Сибирский государственный университет науки и технологий; 2021. С. 685–687. https://elibrary.ru/yjchna

7. Носова С.А., Турлапов В.Е. Детектирование клеток мозга в оптической микроскопии на основе текстурных характеристик методами машинного обучения. *Программирование*. 2019;4:36–45. https://doi.org/10.1134/S0132347419040058
8. Хамад Ю.А., Зотин А.Г., Симонов К.В., Медиевский А.В., Чижова Т.Г. Обнаружение и оценка патологии молочной железы на основе нечеткой кластеризации и дискретного вейвлет преобразования. *Медицина и высокие технологии*. 2023;2:5–13. https://www.elibrary.ru/ujqlwd
9. Raja R., Ganeshkumar P. QoSTRP: надежный протокол маршрутизации на основе кластеризации для мобильных самоорганизующихся сетей. *Программирование*. 2018;6:28–41. https://doi.org/10.31857/S013234740002763-4
10. Кучуганов А.В., Кучуганов В.Н., Осколков П.П., Касимов Д.Р. Аппроксимация цветных изображений на основе кластеризации цветовой палитры и сглаживания границ сплайнами и дугами. *Программирование*. 2018;5:3–11. https://doi.org/10.31857/S013234740001211-7
11. Берешполов И.С., Кравченко Ю.А., Слепцов А.Г. Алгоритм кластеризации данных для защиты конфиденциальной информации в сети интернет. *Известия ЮФУ. Технические науки*. 2023;3(233):74–85. https://doi.org/10.18522/2311-3103-2023-3-74-85
12. Харахинов В.А., Сосинская С.С. Исследование способов кластеризации деталей машиностроения на основе нейронных сетей. *Программная инженерия*. 2017;8(4):170–176. https://doi.org/10.17587/prin.8.170-176
13. Кучуганов В.Н., Кучуганов А.В., Касимов Д.Р. Алгоритм кластеризации множества деталей по чертежам. *Программирование*. 2020;46(1):29–38. https://doi.org/10.31857/S0132347420010045
14. Матвеева И.Ю. Кластеризация розничных инвесторов и структура портфеля по классам активов. *Известия Санкт-Петербургского государственного экономического университета*. 2023;4(142):180–184. https://www.elibrary.ru/fnmsql
15. Батрасова А.Д., Коновалова Т.В., Комаров П.И. Кластеризация как метод исследования финансовой устойчивости IT-компаний. *Управленческий учет*. 2022;(1-2):177–182. https://www.elibrary.ru/xaufce
16. Анфёров М.А. Формализация поиска структурных решений в САПР ТП. В сб.: *Информатика*: *проблемы, методы, технологии*: *Материалы XXII Международной научно-практической конференции.* Воронеж, Воронежский государственный университет, 10–12 февраля 2022 г. Воронеж: ВЭЛБОРН. 2022. С. 881–886. https://elibrary.ru/dsdxhp
17. Яковлев Д.Д., Петров Д.Ю. Применение разведочного анализа данных для кластеризации структур робототехнических сборочных комплексов. *Автоматизированное проектирование в машиностроении.* 2024;17:71–75. https://doi.org/10.26160/2309-8864-2024-17-71-75
18. Степанов М.А. Методика выявления структурных трансформаций временных рядов с использованием принципов нечеткой кластеризации. *Вестник Рязанского государственного радиотехнического университета*. 2019;69:149–159. https://doi.org/10.21667/1995-4565-2019-69-149-159
19. Кладов Д.Е., Бериков В.Б., Климонтов В.В. Алгоритм кластеризации временных рядов и его применение для анализа гликемических кривых. В сб.: *ЗНАНИЯ – ОНТОЛОГИИ – ТЕОРИИ*: *Материалы IX Международной конференции.* Новосибирск, 02–06 октября 2023 г. Новосибирск: Институт математики им. С.Л. Соболева СО РАН; 2023. С. 154–161. https://elibrary.ru/qqzzvw
20. Тищенко А.К., Плисс И.П. Сегментация многомерных нестационарных временных рядов с помощью метода нечеткой кластеризации. *Восточно-европейский журнал передовых технологий*. 2012;4(58):24–26. URL: https://cyberleninka.ru/article/n/segmentatsiya-mnogomernyh-nestatsionarnyh-vremennyh-ryadov-s-pomoschyu-metoda-nechetkoy-klasterizatsii. Дата обращения 02.02.2025. / Accessed February 02, 2025.
21. Дуля И.С. Применение методов глубокого обучения к задаче кластеризации временных рядов. *Аллея науки.* 2021;1(5):974–978. https://elibrary.ru/nokchy
22. Hurley C., Mclean J. *Wavelet Analysis and Methods.* Waltham Abbey: ED-Tech Press; 2021, 366 p.
23. Спирина П.В., Семенова А.Р. Кластерный анализ динамики инновационной деятельности субъектов Российской Федерации. *Экономические исследования и разработки*. 2021;8:42–53. https://elibrary.ru/oiqybo
24. Жихалкина Н.Ф. Динамический подход к задаче кластеризации. *Математические структуры и моделирование.* 2000;5:133–139. URL: https://cyberleninka.ru/article/n/dinamicheskiy-podhod-k-zadache-klasterizatsii. Дата обращения 02.02.2025. / Accessed February 02, 2025.
25. Рыжков Д.В. О методах кластеризации динамических временных рядов. В сб.: *Наука. технологии. Инновации*: *Сборник научных трудов XVII Всероссийской научной конференции молодых ученых.* Новосибирск, 04–08 декабря 2023 г. Новосибирск: НГТУ; 2024. С. 178–182. https://elibrary.ru/xykvdt
26. Зайцев Р.Д. Исследование эффективности многомерной кластеризации временных рядов для анализа динамики научно-технического развития. *Перспективы развития информационных технологий*. 2015;25:7–13. https://www.elibrary.ru/uhrwjt
27. Ten Holt G.A., Reinders M.J.T., Hendriks E.A. Multi-dimensional dynamic time warping for gesture recognition. In: *Thirteenth Annual Conference on the Advanced School for Computing and Imaging.* Netherlands: V. 300. 2007, 8 p. URL: https://www.researchgate.net/publication/228740947. Дата обращения 02.02.2025. / Accessed February 02, 2025.
28. Кочетуров А.А., Бацын М.В., Пардалос П.М. Динамика кластерных структур в сетях фондовых рынков. *Журнал новой экономической ассоциации.* 2015;4(28):12–30. https://www.elibrary.ru/vdzrqh
29. Kohonen T. *Self-Organizing Maps.* 3rd ed. Berlin – New York: Springer-Verlag; 2001, 521 p.

30. Анфёров М.А. Кластеризация в принятии решений. *Информационные технологии. Проблемы и решения*. 2020;2(11):97–102. https://www.elibrary.ru/rwddvo
31. Давыдова Г.В., Беликов А.Ю. Методика количественной оценки риска банкротства предприятий. *Управление риском*. 1999;3:13–20. https://www.elibrary.ru/tdgdrb

## About the Author

**Mikhail A. Anfyorov,** Dr. Sci. (Eng.), Professor, Department of Domain-Specific Information Systems, Institute for Cybersecurity and Digital Technologies, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: anfyorov@inbox.ru. RSCI SPIN-code 4829-2523, https://orcid.org/0000-0003-2853-6184

## Об авторе

**Анфёров Михаил Анисимович,** д.т.н., профессор, кафедра «Предметно-ориентированные информационные системы», Институт кибербезопасности и цифровых технологий, ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: anfyorov@inbox.ru. SPIN-код РИНЦ 4829-2523, https://orcid.org/0000-0003-2853-6184

*Translated from Russian into English by Lyudmila O. Bychkova*
*Edited for English language and spelling by Dr. David Mossop*