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Energy System Monitoring Based on Fuzzy Cognitive Modeling and Dynamic Clustering

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Abstract: A feature of energy systems (ESs) is the diversity of objects, as well as the variety and manifold of the interconnections between them. A method for monitoring ESs clusters is proposed based on the combined use of a fuzzy cognitive approach and dynamic clustering. A fuzzy cognitive approach allows one to represent the interdependencies between ESs objects in the form of fuzzy impact relations, the analysis results of which are used to substantiate indicators for fuzzy clustering of ESs objects and to analyze the stability of clusters and ESs. Dynamic clustering methods are used to monitor the cluster structure of ESs, namely, to assess the drift of cluster centers, to determine the disappearance or emergence of new clusters, and to unite or separate clusters of ESs.

Keywords: energy system; monitoring; fuzzy cognitive model; dynamic clustering

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1. Introduction

Energy systems (ESs) are complex systems characterized by the heterogeneity of subsystems and objects, as well as the variety and diversity of interconnections and interdependencies between them. Moreover, the unification of objects in an ESs is determined by its integration properties, including territorial localization, logistic and commercial interaction of objects, profile specializations, and competitive advantages as a result of interactions [1–3].

In the process of ESs functioning, an inevitable change occurs in various production and technological, commercial, territorial, logistic, and other relationships and interdependencies between system objects.

Moreover, the ESs functioning often takes place in conditions of limited financial, time, and labor resources [4]. This, in turn, leads to a rather strict requirement to the methods and models of analysis and modeling of these systems.

There are various approaches and methods for monitoring energy systems [5,6]. However, the complexity of applying these methods is related to the fact that in the process of operation and development of ESs, production and technological, commercial, territorial, logistic, and other interrelationships and interdependencies between ESs objects change significantly, which leads to the relevance of solving grouping problems, assessing the consistency of interacting objects, monitoring and analyzing their stability of groups of interacting objects [7–10].

In terms of increasing ESs objects interdependence and complexity, united by different interrelations into clusters, the actual tasks of stability analysis and monitoring the dynamics of changes in such clusters cannot be well performed using standard methods. These problems are caused by a large number of heterogeneous indicators, the uncertainty of systemic and external factors, and the vagueness of information. This allows for the solving of these problems to substantiate the practicability of joint use of fuzzy cognitive models ([11]) and dynamic clustering methods [12].

The use of a fuzzy cognitive approach is the basis for the effective solution of these problems, first of all, due to the presentation of interdependencies between ESs objects in the form of fuzzy impact relations.

The most common fuzzy cognitive models are fuzzy cognitive models of B. Kosko [13] and their varieties [14]; fuzzy rule-based cognitive models [15] and generalized rule-based fuzzy cognitive models [16]; fuzzy cognitive models of V. Silov [17].

The systems analysis based on fuzzy cognitive maps can be both static and dynamic. Static analysis consists of studying the mutual influences structure, identifying the problem; searching the most significant factors; checking the achievability of goals; comparing the behavior of the situation under various input influences (scenario analysis); determining the control actions to transfer the situation to the target state. Dynamic analysis consists of simulation modeling, the study of the processes of influences propagation along a fuzzy cognitive map in time.

An important task of fuzzy cognitive modeling is to analyze the stability of systems.

The fuzzy cognitive approach allows for the use of methods of fuzzy causal algebra for preliminary analysis of ESs.

Subsequently, the results of fuzzy cognitive analysis are used to select clustering indicators based on agreed fuzzy impact relations between ESs objects. These indicators are used to identify ESs clusters and assess their sustainability.

For ESs clustering, an approach based on the unsupervised optimal fuzzy clustering algorithm(UOFC) is used, which allows to determine clusters with an arbitrary shape. An adaptive feasible variation of this algorithm is applied.

Further, the methods of dynamic clustering [18] allow monitoring the dynamics of the cluster ESs structure, including the drift analysis of cluster centers, the disappearance and appearance of new clusters, and their unification and separation.

2. Problem Statement of Energy System Monitoring

The statement of a problem of the ESs monitoring is presented as follows:

The prerequisites listed below are accepted.

- The set of ESs objects is considered:

$$A = \{a_i | i = 1, \ldots, I\};$$

- These ESs objects are connected by fuzzy impact relations with all other ESs objects:

$$R = \left\{ \left(r(a_i, a_j) / (a_i, a_j) \right) \middle| r(a_i, a_j) \in [-1, 1],\ a_i, a_j \in A \right\};$$

- There are indicators based on fuzzy impact relations between ESs objects:

$$P = \{p_k | k = 1, \ldots, K\},$$

which specify the conformity of these ESs objects to different clusters:

$$C = \{c_l | l = 1, \ldots, L\};$$

- With a given frequency, the monitoring of fuzzy impact relations R between ESs objects from the A is performed, then the values of fuzzy impact relations are actualized.

It is required to solve the following tasks:

- To justify the indicators based on the fuzzy impact relations between ESs objects and allowing the estimation of the conformity of these ESs objects to different clusters;
- To design a model to, firstly, analyze the fuzzy impact relations between ESs objects and identify ESs clusters and, secondly, estimate the accordance degree of ESs objects with clusters based on the indicators values from a justified set;
- To propose a method based on the developed model, which allows the evaluation of the stability and monitoring cluster dynamics.

3. Analysis of Fuzzy Impact Relations between Objects and Identification of Energy System Clusters

In [19], a method for analyzing fuzzy impact relations on the basis of a fuzzy cognitive approach is considered, and a set of indicators for identifying system clusters is substantiated. This method includes the following steps.

Step 1. Setting concepts of a fuzzy cognitive model corresponding to ESs objects

$$A = \{a_i | i = 1, \ldots, I\},$$

For example, the various options for specifying a concepts set are possible, depending on the description and strategy of the solving:

- Firstly, the concepts can correspond to the ESs objects;
- Secondly, the concepts can correspond to the ESs objects of some initially formed cluster $c_l \in C$.

Step 2. Specifying fuzzy impact relations between concepts,

$$R = \left\{ \left(r(a_i,\ a_j) / (a_i,\ a_j) \right) \middle| r(a_i, a_j) \in [-1, 1], a_i, a_j \in A \right\}.$$

Relation R is represented as an adjacency matrix $\mathbf{R} = \|r_{ij}\|_{I \times I}$, where $r_{ij} \in [-1, 1]$—the degree of influence of the concept-source a_i on the concept-receiver a_j, I—number of model concepts.

These fuzzy impact relations are set either by experts or as a result of experimental research in the form of directional weighted arcs between each pair of concepts of fuzzy cognitive model.

Step 3. Converting a matrix $\mathbf{R}$ to a matrix of non-negative values $\mathbf{Q} = \|q_{ij}\|_{2I \times 2I}$:

$$\mathit{If}\ r_{ij} > 0,\ \mathit{Then}\ q_{2i-1,2j-1} = r_{ij}\ \mathit{and}\ q_{2i,2j} = r_{ij},$$

$$\mathit{If}\ r_{ij} < 0,\ \mathit{Then}\ q_{2i-1,2j-1} = -r_{ij}\ \mathit{and}\ q_{2i,2j} = -r_{ij}.$$

Step 4. Matrix matching $\mathbf{Q}$ based on transitive closure:

$$\overset{\frown}{\mathbf{Q}} = \mathbf{Q} \vee \mathbf{Q}^2 \vee \mathbf{Q}^3 \vee \ldots.$$

Matrices $\mathbf{Q}$, $\mathbf{Q}^2$, $\mathbf{Q}^3$, ... are calculated based on the operation of max-prod-composition, the operation "$\vee$" is used as the operation max.

Transitive closure guarantees the stability of the simulated cluster and the correct calculation of the selected system indicators.

If it is not possible to achieve the transitive closure of the matrix $\mathbf{Q}$, then the model is unstable, and, if necessary, the possibility of bringing it to a stable state is determined.

Step 5. Matrix transformation $\overset{\frown}{\mathbf{Q}}$ into matrix $\mathbf{R}' = \|r'_{ij}, \bar{r}'_{ij}\|_{I \times I}$, specifying the coherent fuzzy impact relations between the ESs objects:

$$r'_{ij} = \max\left(q_{2i-1,2j-1}, q_{2i,2j}\right),\ \bar{r}'_{ij} = -\max\left(q_{2i-1,2j}, q_{2i,2j-1}\right)$$

Step 6. The choice of indicators for the ESs clusters identification based on coherent fuzzy impact relations.

In papers [15,17], the method to study complex systems and processes is considered, which is based on the analysis of fuzzy impact relations of between their systemic factors (concepts). The following indicators can be used for the analysis, based on fuzzy impact relations between ESs objects:

- The impact indicator of one ESs object on another ESs object;
- The mutual positive impact indicator of ESs objects on each other;
- The mutual negative impact indicator of ESs objects on each other;
- The indicator of the impact consonance of one ESs object on another ESs object;
- The indicator of the impact dissonance of one ESs object on another ESs object;

- The indicator of the mutual impact consonance of ESs objects on each other;
- The indicator of the mutual impact dissonance of ESs objects on each other;
- The impact indicator of a separate ESs object on clusters as a whole;
- The impact indicator of clusters on a separate ESs object;
- The indicator of the impact consonance of a separate ESs object on clusters;
- The indicator of the impact dissonance of a separate ESs object on clusters;
- The indicator of the impact consonance of clusters on a separate object of the ESs;
- The indicator of the impact consonance of clusters on a separate object of the ESs and the impact dissonance of clusters on a separate object of the ESs;
- The indicator of the impact consonance of clusters on a separate object of the ESs and the mutual consonance of a separate ESs object and ESs clusters;
- The indicator of the impact consonance of clusters on a separate object of the EsS and the mutual dissonance of a separate ESs object and ESs clusters.

From the set of system indicators for the ESs clusters identification in [17], the following indicators were selected:

- The impact indicator of a separate ESs object on clusters as a whole

$$p_1(a_i) = \frac{1}{I}\sum_{j=1}^{I}\left(\mathrm{sign}\left(r'_{ij} + \bar{r}'_{ij}\right)\max\left(\left|r'_{ij}\right|, \left|\bar{r}'_{ij}\right|\right)\right),\ i = 1\ldots I;$$

- The impact indicator of clusters on a separate ESs object

$$p_2(a_i) = \frac{1}{I}\sum_{j=1}^{I}\left(\mathrm{sign}\left(r'_{ij} + \bar{r}'_{ij}\right)\max\left(\left|r'_{ij}\right|, \left|\bar{r}'_{ij}\right|\right)\right),\ i = 1\ldots I;$$

- The indicator of the impact consonance of a separate ESs object on clusters

$$p_3(a_i) = \frac{1}{I}\sum_{j=1}^{I}\frac{\left|r'_{ij} + \bar{r}'_{ij}\right|}{\left|r'_{ij}\right| + \left|\bar{r}'_{ij}\right|},\ i = 1\ldots I.$$

Step 7. Preliminary clustering of objects and identification of ESs clusters.

For clustering of ESs objects, a hierarchical agglomerative method is used, which makes it possible to form a dendrogram of the ESs objects separation, illustrating the dependence of the clustering quality on the number of clusters. In addition to this method, the method of silhouettes is also used, where the average value of the width of all "silhouettes" of clusters is used as an indicator of the quality of clustering [20].

The problem of identifying ESs clusters is considered to be successfully solved if the maximum value of the clustering quality indicator is reached.

Step 8. Preliminary analysis of the ESs clusters' stability.

The analysis of the ESs clusters' stability consists in the analysis of the results of the transitive closure of fuzzy impact relations between the objects of each of the identified ESs clusters. The conclusion about the ESs clusters' stability is made on the basis of the rule: The degree of each ESs cluster's stability depends on the ratio of the number of iterations of the transitive closure procedure to the number of cluster objects. The smaller it is, the more stable this cluster is [19].

Based on the results of the analysis of fuzzy impact relations between the ESs objects, the following tasks are solved:

- The choice of indicators for identifying ESs clusters;
- Preliminary clustering of objects and identification of ESs clusters;
- Preliminary analysis of the ESs clusters' stability.

4. Monitoring the Dynamics of Changes in the Energy System Cluster Structure

After preliminary identification of ESs clusters, it is advisable to use one of the fuzzy clustering methods, which makes it possible to determine the fuzzy degrees of membership of objects to ESs clusters.

To monitor the dynamics of changes in the cluster structure of ESs, methods of fuzzy clustering are used, which make it possible to determine the fuzzy membership degrees for objects to clusters.

Monitoring the dynamics of changes in ESs clusters consists in analyzing changes in the cluster structure of ESs. This analysis assumes the solution of the following tasks: analysis of the drift (location) of cluster centers; disappearance of clusters; the new clusters emergence; combining clusters; separation of clusters.

In the monitoring process, at each moment of the model time, the stability of the changing cluster structure of the ESs is also assessed.

Taking into account fuzziness when performing clustering allows to consider the different membership degrees of ESs objects to different clusters.

Based on the results of the applicability analysis for various methods of fuzzy clustering, the following conclusions were made. Using the fuzzy C-means method of fuzzy clustering often leads to incorrect results when the clusters differ in shape [21]. The *UOFC* method is devoid of this drawback, which is a combination of the fuzzy C-means method and the improved maximum likelihood method [18].

A feature of the formulation and solution of the problem of monitoring the dynamics of changes in ESs clusters is that the source of information is the change in the values of fuzzy impact relations between ESs objects. At the same time, monitoring consists at each moment of the model time:

- Firstly, in the analysis of changes in the ESs cluster structure, including the analysis of the cluster centers' drift, the disappearance and appearance of new clusters, their unification and separation;
- secondly, in the analysis of the ESs clusters stability based on the assessment of the results of transitive closure of fuzzy impact relations between ESs objects.

5. An Example of Monitoring the Dynamics of Changes in Energy System Clusters

The proposed method was tested using the example of energy system monitoring in the Smolensk region (Russian Federation).

As a result of the research, a lot of ESs objects were identified (in the example of the Smolensk region), a fuzzy cognitive model was built, and on the basis of the coherent fuzzy impact relations between its objects, the values of the indicators were calculated to identify the clusters of this system (Table 1) [19].

Figure 1 shows the dendrogram of the division of ESs objects in the Smolensk region, and Figure 2 shows the clustering quality dependence on the number of ESs clusters.

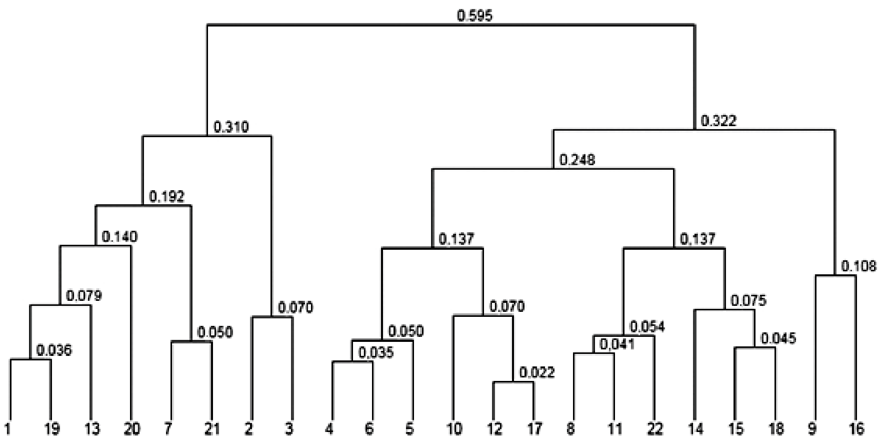


Figure 1. Dendrogram for the objects separation in ESs in the Smolensk region.

Table 1. Values of indicators for identification of clusters in the Smolensk region ES.

Objects of the Energy System	**Desnogorsk Energy College**	**The Branch of NRU "MPEI" in Smolensk**	**Smolensk NPP**	**Smolenskaya GRES**	**Smolensk TPP-2**	**Dorogobuzhskaya TETS**	**Smolenskteploset**	**Dorogobuzh Thermal Management**	**GIDROSTROY**	**Firm Energo+**	**Turbopar**	**Energomontazhavtomatika-EP**	**Analitpribor**	**ABO Valves**	**Stroykomplekt-Emal**	**Globus-Services**	**TD "Automation"**	**Dorogobuzhkotlomash**	**Smolenskenergo**	**Branch "Smolenskenergosbyt"**	**RUSELPROM-FEZ**	**Energoprommarket**
	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	a_{20}	a_{21}	a_{22}
$p_1(a_i)$	0.329	0.448	0.505	0.218	0.209	0.215	0.230	0.145	0.123	0.137	0.143	0.142	0.334	0.145	0.122	0.023	0.162	0.162	0.351	0.284	0.202	0.172
$p_2(a_i)$	0.309	0.330	0.307	0.237	0.272	0.223	0.263	0.183	0.114	0.204	0.199	0.175	0.237	0.153	0.096	0.106	0.165	0.099	0.309	0.330	0.271	0.223
$p_3(a_i)$	0.678	0.692	0.659	0.512	0.491	0.480	0.675	0.612	0.348	0.474	0.649	0.420	0.645	0.667	0.623	0.376	0.422	0.643	0.649	0.552	0.715	0.610

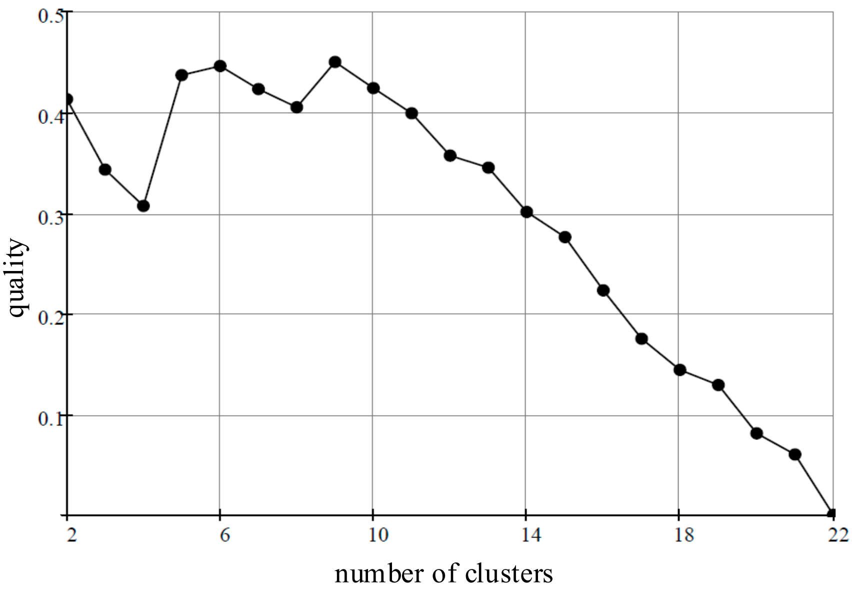
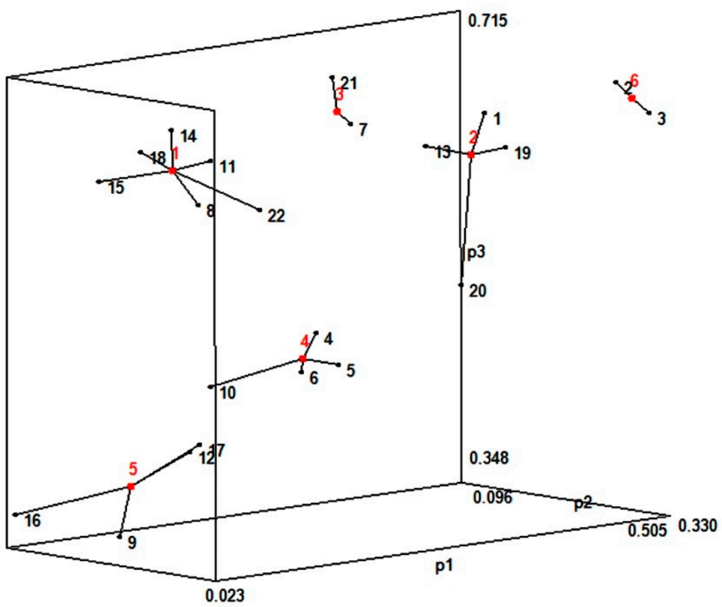


Figure 2. Dependence of the quality of clustering on the number of ESs clusters.

Fix a partition of objects in the Smolensk region ESs at six clusters: c_1: $\{a_1, a_{13}, a_{19}, a_{20}\}$; c_2: $\{a_7, a_{21}\}$; c_3: $\{a_2, a_3\}$; c_4: $\{a_4, a_5, a_6, a_{10}, a_{12}, a_{17}\}$; c_5: $\{a_8, a_{11}, a_{14}, a_{15}, a_{18}, a_{22}\}$; c_6: $\{a_9, a_{16}\}$.

Figure 3 shows the objects location and identified clusters centers, and Table 2 represents the matrix of membership degrees of objects to the corresponding clusters of the ESs in the Smolensk region.



cluster	cluster center		
	p_1	p_2	p_3
1	0.146	0.152	0.636
2	0.331	0.292	0.644
3	0.214	0.265	0.687
4	0.202	0.239	0.493
5	0.113	0.140	0.392
6	0.476	0.319	0.675

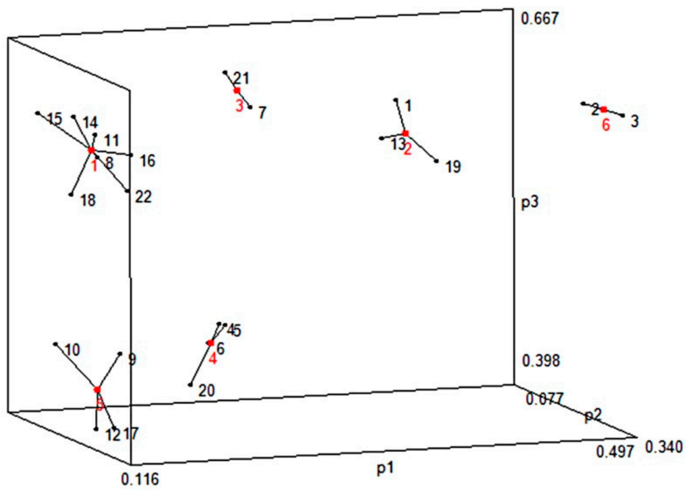
Figure 3. Results of preliminary clustering of objects in the Smolensk region ESs.

Transitive closure of matrix **Q** converged in four iterations (<<*I*), which indicates the stability of the ESs of the Smolensk region. This is true for all identified ESs clusters.

Figures 4–7 represent the process of changing the cluster structure of the ESs in the Smolensk region (in 2020 with a frequency of two months).

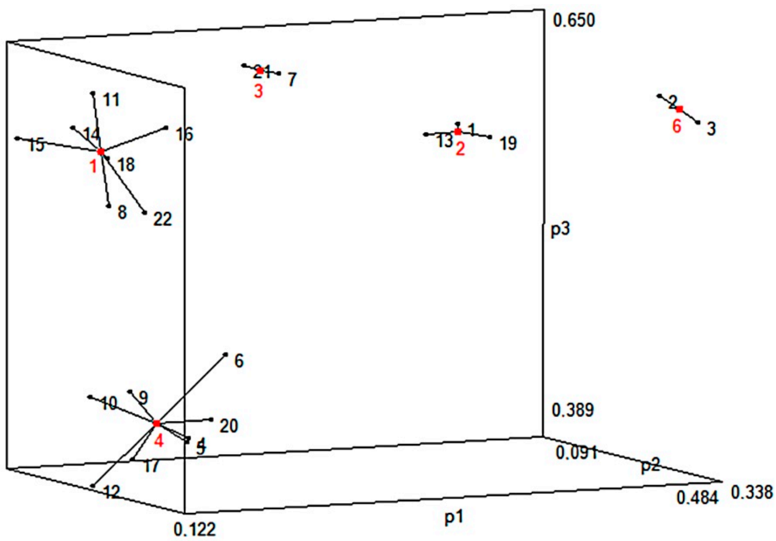
Table 2. Matrix of membership degrees of objects to identified clusters of ESs in the Smolensk region.

Clusters	Objects																					
	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	a_{20}	a_{21}	a_{22}
1	0.005	0.004	0.005	0.011	0.024	0.022	0.031	0.022	**0.875**	0.277	0.010	**0.752**	0.019	0.019	0.016	**0.680**	**0.681**	0.007	0.005	0.055	0.038	0.011
2	0.035	**0.908**	**0.930**	0.004	0.008	0.005	0.055	0.009	0.008	0.019	0.005	0.010	0.084	0.011	0.005	0.021	0.013	0.003	0.050	0.097	0.063	0.006
3	**0.917**	0.060	0.038	0.010	0.020	0.011	0.317	0.024	0.014	0.041	0.016	0.019	**0.721**	0.028	0.011	0.035	0.025	0.008	**0.902**	**0.348**	0.248	0.021
4	0.014	0.010	0.010	**0.947**	**0.899**	**0.928**	0.102	0.052	0.051	**0.452**	0.023	0.138	0.059	0.035	0.020	0.106	0.181	0.011	0.016	0.294	0.098	0.043
5	0.010	0.007	0.007	0.010	0.017	0.013	0.110	0.202	0.027	0.090	0.091	0.039	0.044	**0.604**	**0.888**	0.085	0.049	**0.932**	0.010	0.067	0.142	0.048
6	0.019	0.010	0.010	0.019	0.032	0.021	**0.386**	**0.692**	0.025	0.121	**0.855**	0.042	0.075	0.303	0.060	0.073	0.051	0.039	0.017	0.139	**0.412**	**0.870**



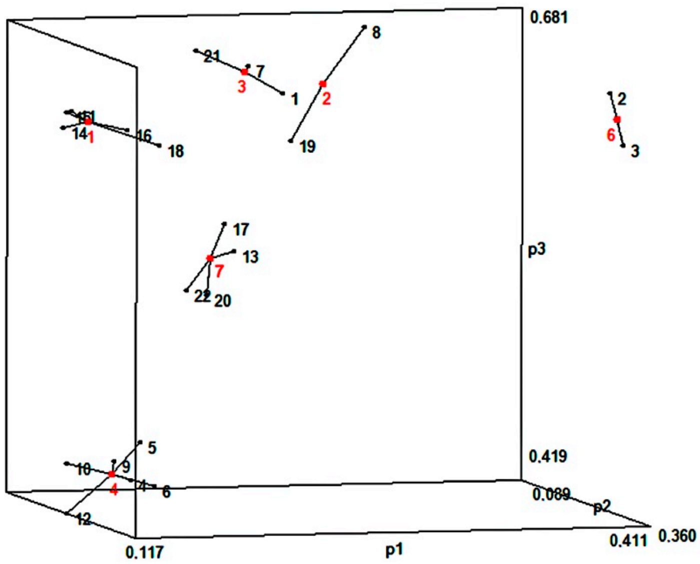
cluster	cluster center		
	p_1	p_2	p_3
1	0.153	0.153	0.595
2	0.339	0.295	0.619
3	0.219	0.277	0.653
4	0.207	0.252	0.469
5	0.146	0.184	0.429
6	0.477	0.325	0.632

Figure 4. Clustering results of ESs objects at the moment of model time $t = 1$.



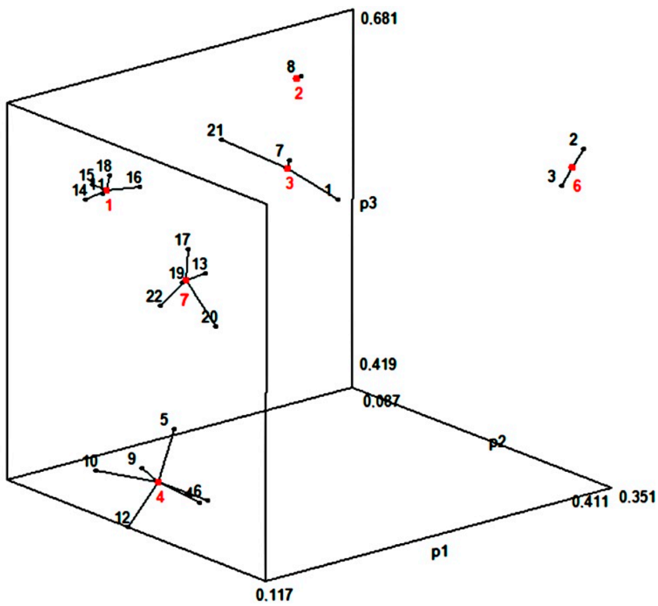
cluster	cluster center		
	p_1	p_2	p_3
1	0.157	0.150	0.588
2	0.329	0.291	0.607
3	0.211	0.259	0.647
4	0.166	0.210	0.427
6	0.463	0.322	0.617

Figure 5. The results of clustering of ESs objects at the time $t = 2$.



cluster	cluster center p_1	cluster center p_2	cluster center p_3
1	0.146	0.151	0.629
2	0.275	0.171	0.650
3	0.203	0.271	0.668
4	0.145	0.210	0.440
6	0.399	0.330	0.642
7	0.214	0.162	0.554

Figure 6. The results of clustering of ESs objects at the time $t = 3$.



cluster	cluster center p_1	cluster center p_2	cluster center p_3
1	0.146	0.153	0.631
2	0.296	0.167	0.679
3	0.203	0.269	0.665
4	0.145	0.208	0.443
6	0.399	0.325	0.638
7	0.210	0.157	0.556

Figure 7. The results of clustering of ESs objects at the time $t = 4$.

Based on the obtained results of monitoring the dynamics of changes in the clusters in the Smolensk region ESs, it can be concluded:

- By the moment of time $t = 1$, object a_{10} moves out of the cluster c_4 into the cluster c_5, object a_{16}—from the cluster c_5 into the cluster c_1, object a_{20}—from the cluster c_2 into the cluster c_4; the drift of the centers of all clusters is noticeable, while the c_5 cluster center drifts to the greatest extent;
- By the moment of time $t = 2$, cluster c_4 and cluster c_5 unite;
- By the time $t = 3$, object a_1 moves into the cluster c_3, object a_8—into the cluster c_2; a new cluster c_7 appears, consisting of objects $\{a_{13}, a_{17}, a_{20}, a_{22}\}$;
- By the time $t = 4$, the object a_{19} also moves into the cluster c_7.

6. Conclusions

The article proposes an original formulation of the monitoring ESs problem. The monitoring of ESs clusters is suggested based on a combination of a fuzzy cognitive approach and dynamic clustering methods. A fuzzy cognitive approach allows one to represent various interdependencies between ESs objects in the form of fuzzy impact relations, thus provides the possibility of using fuzzy causal algebra for preliminary analysis of ESs.

Analysis of fuzzy mutual impact relations between ESs objects consists of: (i) Setting the concepts of a fuzzy cognitive model corresponding to ESs objects; (ii) transforming the matrix of fuzzy impact relations into a matrix of non-negative values; (iii) matching the resulting matrix of non-negative values based on transitive closure; (iv) transformation of a transitively closed matrix into a matrix that specifies coordinated fuzzy impact relations between ESs objects; (v) selection of indicators for the identification of ESs clusters, based on consentient fuzzy impact relations.

The results of the analysis of fuzzy impact relations, in turn, are used to substantiate a set of indicators for the identification and subsequent monitoring of the dynamics of changes in the ESs cluster structure, as well as to analyze the stability (based on the assessment of the results of transitive closure of fuzzy impact relations between their objects) of identified clusters and ESs on the whole.

The following indicators were selected for identifying ESs clusters: The impact of the object on the ESs; the impact of the ESs on the object; the coherent impact of the object on the ESs.

The conclusion about the ESs cluster stability is made on the basis of the rule: The ESs cluster stability degree depends on the ratio of the transitive closure procedure iterations number to the number of cluster objects. The smaller it is, the more stable this cluster is.

The idea of the proposed approach for monitoring ESs is based on the fact that, in the ESs functioning process, it is the fuzzy impact relations between ESs objects that change.

To monitor the dynamics of changes in the ESs cluster structure, methods of fuzzy clustering are used, which make it possible to determine the fuzzy membership degrees of objects to clusters. Monitoring the dynamics of changes in ESs clusters consists of analyzing changes in the ESs cluster structure, including the analysis of the drift of cluster centers, the disappearance and appearance of new clusters, and their merging and separation. In the process of monitoring, at each moment of the model time, the stability of the variable cluster structure of the ESs is also assessed.

Thus, the convergent combination of fuzzy cognitive modeling and dynamic clustering gives a synergistic effect for a new quality of ESs research.

An example of monitoring the dynamics of changes in clusters ing the Smolensk region ESs based on a combination of a fuzzy cognitive approach and methods of dynamic clustering is presented.

The proposed approach development consists of the construction of fuzzy cognitive models for various sets of ESs objects, with the subsequent comparison of the corresponding models' stability conditions, as well as the analysis of the system characteristics of these objects and the dynamics monitoring of changes in the clusters identified on their basis.

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