Case Based Reasoning for managing urban infrastructure complex technological objects

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Abstract. Modern urban infrastructure systems are complex technological objects. The stability of their work is important not only for life support systems, but also for the safety of people and nature. The systems are supported by monitoring and prompt troubleshooting. Dangerous situations at complex technological facilities can have fatal consequences for humans, nature and infrastructure. A high level of responsibility, together with a variety of possible situations at a complex technological facility, determines the relevance of the tasks of intellectual support for decision-making. At the same time, there are not enough data volumes for machine learning of such systems. The use of hybrid artificial intelligence models that combine both machine learning and knowledge-based inference methods is promising. The authors of the article investigate the possibilities of creating hybrid models based on the general idea of the case based reasoning (CBR) method. To implement the CBR method, an ontological model of a complex technological object is proposed in the work. On this basis, a formalized representation of situations on a complex object has been developed, an approach has been proposed for identifying and selecting situations, which takes into account their structural and parametric proximity. The work provides a basis for further development of algorithmic and software for the in-demand systems for intelligent management of urban infrastructure facilities using CBR, fuzzy logic and neural networks.

Keywords: Case-based reasoning, Intelligence monitoring, Decision support systems, City infrastructure

1 Introduction

Modern urban infrastructure systems (power supply, gas, water, heat supply systems) are complex technological objects (CO). The safety and stability of the processes taking place in them are important not only for the life support of the city, but also for the preservation of the ecology, health and lives of people.

System operability support is carried out by monitoring the state of their elements and prompt troubleshooting. In the modern world, these tasks are solved by creating digital systems for the "smart city" and "smart industries". The tasks of monitoring complex objects in order to prevent emergencies are relevant both for enterprises providing heat, water, gas, energy supply to the region, and for security services and city management.

Most of the modern works in the field of monitoring technological processes and objects are devoted specifically to the problem of collecting primary data in real time, the completeness and accuracy of which allow making a conclusion about the state of the monitoring object. A significant part of publications is devoted to the technical aspect of the problem (sensors, ultrasound diagnostics, etc.) [1-5], there are proposals on the use of data mining methods and (or) neural networks to identify emergency situations [6-9].

These methods, however, require a significant amount of training data (examples of situations); in the case of a complex monitoring object, there may not be such data representing all emerging situations. Another area of work is associated with the creation of knowledge-based systems, expert advice and decision support systems [10-13]. At the same time, the laboriousness of identifying and formalizing knowledge limits the use of these methods to relatively simple objects and situations.

In urban infrastructure systems, two interrelated tasks arise: monitoring with the identification of potentially dangerous situations and decision-making to prevent dangerous situations and eliminate their consequences.

Dangerous emergencies at complex technological facilities, as a rule, develop in different conditions (temporary, climatic, organizational), under different conditions of both the facility itself and its diverse environment. This gives rise to significant uniqueness in such situations. And if it is possible to recognize a critical situation in the monitoring process by controlling the parameters and using machine learning methods, then the choice of effective actions to resolve it and prevent the consequences becomes a nontrivial task.

To ensure the safety and efficiency of the functioning of urban infrastructure, it is necessary to comprehensively consider monitoring tasks and decision-making tasks. The authors believe that this requires a hybrid approach that combines methods of traditional symbolic artificial intelligence systems (in particular, knowledge-based systems) and methods of neurointelligence and machine learning.

The Case Based Reasoning (CBR) method is considered as the basis for such a combination. The CBR method involves accessing the database and selecting a use case - a solution to a previously fixed problem that will be used for a new, current problem. At the same time, solutions of previously fixed problems known from experience can adapt to the current situation.

Case based reasoning is widely used in various subject areas. One of the promising areas is associated with decision-making in the management of complex technical and organizational-technical objects [14-16]. At the same time, due to the complexity and diversity of the objects under consideration, as well as the conditions of their functioning, each problem area still requires its own research, starting with the search for models for formalizing the representation of objects and continuing with algorithms for inference and adaptation of solutions based on situation analysis.

The purpose of this work is to develop a model for representing a complex technological object of urban infrastructure, focused on the use of the case-based reasoning method for preventing and eliminating the consequences of dangerous situations. Within the framework of this goal, the article first describes the content and stages of the CBR method, then describes the representation of a generalized complex object through the elements, their states and relationships between them, and proposes an ontological model of such an object. Then, on the basis of this model, a formalized representation of situations arising at a technological facility was developed, which allows comparing situations with each other and selecting similar situations. Further, an approach and metrics of the proximity of situations are proposed, taking into account both the parameters and the structure of situations on a complex object. After that, the results were discussed and tasks for further research were proposed.

2 Materials and methods

The developed applied ontology is focused on using the Case-Based Reasoning method. The method allows solving a new unknown problem using or adapting the experience of solving an already known problem [17].

The CBR system provides for the creation of a case base (BP), each of which is a pair: a situation that required its own decision, and a decision that was made in this situation. The BP may include all the precedents from practice or only those that contain solutions that are found to be effective.

The main stages of withdrawal in the CBR system are:

- Identification of the current situation;
- Extracting precedents from the BP, the situations of which are most similar to the current situation;
- Using solutions from selected use cases for the current situation;
- Analysis of the obtained solution for the current situation and saving the new precedent in the BP for later use.

The tasks of comparing situations and selecting from the base of precedents in the literature on CBR are among the most relevant for the implementation of this method. There are two main approaches to their implementation [17]: selection using metrics and selection by determining the class of the situation using classification trees. The first approach allows you to store in the BP a large number of precedents that arise in practice, without requiring their preliminary classification. The use of classifiers makes it possible to split the entire set of use cases into classes and perform searches in conditions when situations are described by many and varied parameters, which complicates the use of metrics.

However, when solving selection problems, one must not forget about the problem of identifying the current situation. On the one hand, the ability to obtain certain data to characterize the current situation will affect how it will be possible to compare and select situations in the BP. On the other hand, the accepted way of describing the BP situation will determine what data needs to be collected to identify the current situation. Thus, the model of the formalized representation of the situations under consideration is of decisive importance for the stages of inference in a CBR system.

To apply the CBR method in the area under consideration, a formal model for representing situations that arise at a complex technological object is required. At the same time, we assume that a complex technological object includes elements of various types, such as the actual technical devices, software and hardware communication and control systems, servicing and operating organizations (personnel), resources, and other environment. Formally, the state of a complex technological object, its elements and connections between them will be represented by its ontological model. The model should display the composition of the elements of such a complex object, the connections between them, as well as their states. To use the CBR method, by a situation on a complex object, we mean such a state of affairs, which is characterized by the current state of the elements of the object and the connections between them.

3 Results

3.1 Ontological model of a complex object and representation of situations

The structure of the CO contains elements of various types. The elements are highlighted: equipment, personnel, software and information complex, resources, buildings, natural objects and phenomena. The structure, natural objects and phenomena are related to the environment, but at the same time they are considered as part of CO, since they have a connection with CO and are able to influence it.

If necessary, it is possible to single out subsystems CO_1, CO_2, etc. in CO, which, upon a more detailed examination, are also complex technological objects with previously designated elements. Figure 1 shows the constituent elements of a complex technological object of urban infrastructure.

In the ontological representation, a complex *CO* object is described by a quadruple $<O, S, R, A>$, where O is a set of elements. These elements include: equipment, personnel, software and information complex, resources, buildings, natural objects and phenomena; S - set of states:

$$S=\{ S_{ij} \mid \forall_i \in I ; \forall_j \in J_i\}, \quad (1)$$

Where I is the set of indices of the elements of CO; J_i is the set of indices of states of the i-element.

Many typical states include states such as “Running”, “Stopped”, “Healthy”, “Not functional”, “Present”, “Absent”, “Available”, “Not available”, etc., R - many relationships between elements of a complex object:

$$R=\{ R_k \mid \forall_k \in K\}, \quad (2)$$

Where K is a set of indices of relations between elements of CO, contains typical relations Part-of, Has-a, Kind-of, etc. Object-specific relationships can be added; A - a set of axioms - certain necessary combinations of links between the elements of an object.

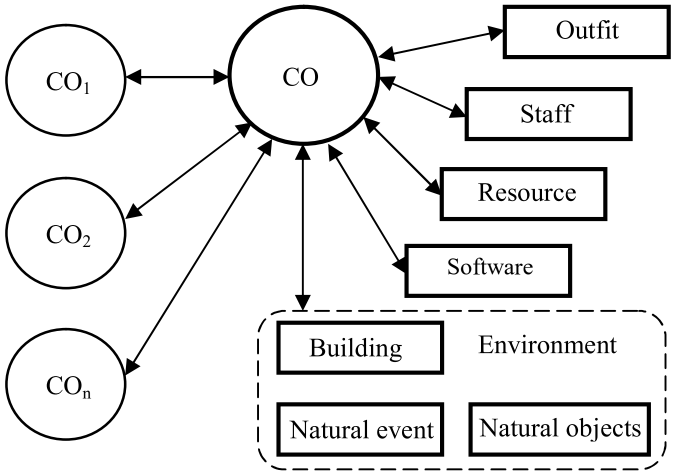

Fig. 1. The constituent elements of a complex technological object.

Figure 2 shows a generalized view of CO. Elements O are associated with a complex technological object by inclusion relations (solid line in the figure) and are interconnected by interaction relations (dashed lines). Each element of O is capable of taking one of the possible states of S.

The considered generalized model of a complex object allows us to introduce a formalized representation of the situation at the object. The Sitz situation is a projection of the ontological model onto a specific setting, where specific values of elements, connections and states are determined: $Sit_z = \langle O_z, S_z, R_z \rangle$, where $O_z \subseteq O$, $S_z \subseteq S$, $R_z \subseteq R$.

3.2 Identification and selection of situations from the base of use cases

To identify and select similar situations, two proximity metrics are used: structural and parametric. Structural proximity reflects similarity in the number of elements and their relationships. Parametric proximity reflects the similarity of the states of elements.

The following approach is proposed to assess the structural similarity. Let us first consider the set of relations on the CO elements. Let us introduce the graph G_k, which will display the k relation on the elements of a complex object. The union of relationship graphs represents the entire set of interaction relationships in the ontological model.

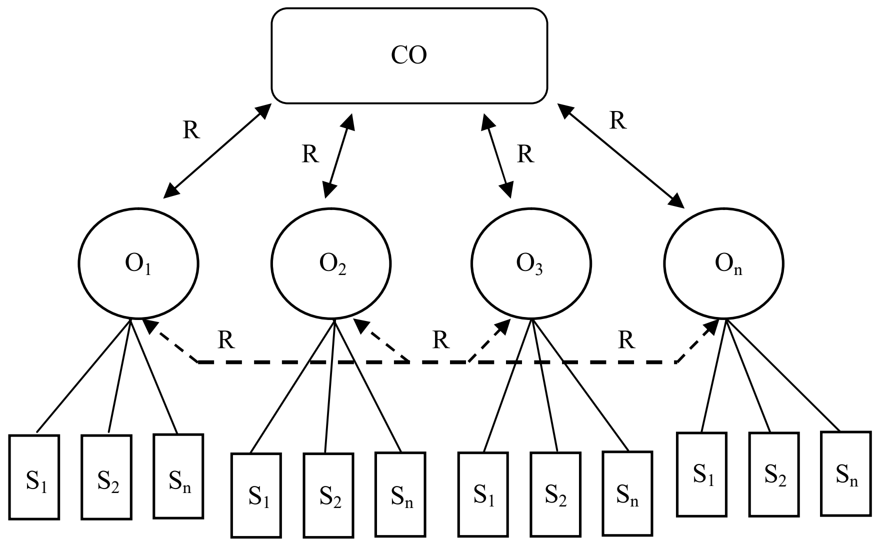

Fig. 2. Generalized presentation of a complex technological object.

We represent the graph of the relation G_k by the adjacency matrix M, in which the cells take on the values 1 - if between the corresponding elements of the object there is a relation from the set R_z and 0 - otherwise.

Let $M_{k,\ act}$ be the matrix of the k relation in the current situation, and $M_{k,\ z}$ be the matrix of the k relation for the z situation in the base of precedents.

Then we can determine the similarity matrix of two situations with respect to R_k:

$$M_k\ (z, act) = M_{k,z} * M_{k,act}, \tag{3}$$

Where * is the operation of element-wise matrix multiplication.

To assess the structural similarity of Sim_k situations with respect to R_k, the following formula is used:

$$Sim_k\ (Sit_Z, Sit_{Act}) = N / \max\ \{N_{act}, N_z\}, \tag{4}$$

Where N is the number of nonzero cells in the matrix M_k (z, act);

N_{act} , N_z is the number of nonzero cells in the matrices $M_{k,\ act}$ and $M_{k,\ z}$ respectively.

Then the overall similarity score is calculated from the weighted sum:

$$Sim\ (Sit_Z, Sit_{Act}) = \sum \alpha\ Sim_k\ (Sit_Z, Sit_{Act}), \tag{5}$$

Where α is the weight coefficient of the k ratio.

When comparing structural similarity, the axioms specified in the set A are taken into account - the minimum necessary relations between elements that should be in similar situations.

The second stage for situations with the highest degree of structural proximity is the assessment of parametric proximity. The sets of states of elements of the object S_z, S_{act} are compared. To assess the parametric proximity, it is proposed to determine the ratio of the number of coincident states to the total number of all states:

$$\mathrm{Sim}(S_z, S_{act}) = N_{\approx} / N \tag{6}$$

Where N≈ is the number of matched states for elements, N is the number of all states in the compared situations.

The issues of identifying and comparing the states of elements of a complex object are beyond the scope of this article. However, it can be noted that the solution of these problems also depends on how the representation of elementary states is formalized. In particular, for this, the previously mentioned approaches used to compare situations can be applied.

Thus, the selection of precedents in the BP is carried out sequentially, in two stages. As a result, the situation is selected from the base of precedents that is closest to the current one, both in the number of elements and connections between the elements of a complex object, and in their states. Together with the situation, a decision related to it is displayed from the database. The solution is used directly or (in case of insufficiently high estimates of proximity) it adapts to the current situation, i.e. is taken as a basis for a prompt search for a solution in the current situation. In this case, the newly obtained precedent is entered into the database.

4 Discussion

The article presents an applied ontological model of a complex urban infrastructure object developed by the authors, on the basis of which a model for representing situations and methods for assessing the proximity of situations for their selection in the base of precedents is proposed. The proposed ontological model is aimed at applying the CBR method to fulfill the tasks of monitoring and resolving dangerous situations. There is a potential for integrating this model with other universal and subject ontologies that can be created to represent knowledge about certain objects of urban infrastructure. Due to this, in the process of deriving solutions, the meaning of specific parameters of objects can be performed and, thus, the identification of states and situations at a complex technological object can be performed.

The proposed CBR approach in the formal representation of the ontological model allows a broader consideration of emerging situations on CO. The inclusion of elements of its environment in the formalized representation of CO allows to take into account, when presenting situations and making decisions, not only the technical aspects of a technological object, but also the influence of many external factors (the state of surrounding objects, organizational systems, climatic conditions, etc.). A comprehensive assessment of the CRM of the urban infrastructure allows us to consider the object also from the point of view of environmental safety, which supports and develops the topic of works [18-19].

Application of the CBR method in ontological representation avoids dependence on a large amount of training data (examples of situations) required when using machine learning methods [6-9]. The ability to adapt precedents from the base for a specific situation reduces the labor costs for identifying and formalizing data for each unique case, which are great when using the expert knowledge method [10-12]. Thus, the model is not limited to simple situations and objects. There is a possibility of "additional training" of the model by adding states and connections to the network and the object.

5 Conclusion

In the course of the study, the following main results were obtained: an applied ontological model of a complex urban infrastructure object was developed, on the basis of this, a model of a formalized representation of situations was proposed, as well as an approach and metrics for comparing and selecting situations, taking into account both their structural and parametric proximity.

Models for representing a complex object and situations are universal and can be used to formalize the presentation of various objects of urban infrastructure. At the same time, the methods for assessing the proximity of situations developed on the basis of these models make it possible to create algorithms for inference decisions that are applicable for a wide class of decision support systems. The implementation of the CBR method using these models provides a basis for performing the complex task of predicting the development of situations and making recommendations to various participants in the CRM management process.

To develop the results obtained, we plan to solve the following tasks: the development of methods for analysis and comparison of states (elements and relations) described in various parametric spaces, as well as generalization of the results obtained for cases of uncertainty in relations between the elements of an object and their states. The results obtained will make it possible to move on to the development of algorithmic and software for the in-demand systems for intelligent management of urban infrastructure facilities using CBR, fuzzy logic and neural networks.

The work is important for the development of the approach of neurosymbolic artificial intelligence as applied to the tasks of managing complex organizational and technical objects.

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