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INFORMATION SEARCH

Onto-Graphic Mechanisms for Deep Semantic Search

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Abstract—In human-machine document retrieval frameworks focused on information support for main activity cognitive processes, onto-graph-based mechanisms for deep semantic search are discussed. The mechanisms of the application of examples corresponding to users' cognitive states are given on graphs constructed from full texts. The paper gives a comparative evaluation of graph search mechanisms effectiveness in retrieval tasks, as applied to text reading processes.

Keywords: information retrieval, deep semantic search mechanisms, text processing, ontologies graph representations

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INTRODUCTION

The purpose of documentary information retrieval is to eliminate a user's problem, i.e., to obtain some answer to a question or some knowledge about the subject area (SbA) of the study from the texts of documents found. The article "From semantic to cognitive information search: Main concepts and models of deep semantic search" [1] has shown that a graph form that contributes to the integration of the analytical and synthetic expression of semantics can be used as an interactive tool for navigating through text and concepts[1] (as a datalogical representation of an ontology built on the text of a document). At the same time, it has been noted that the main purpose of the graph was not so much to give a ready-made answer but to provide access to potentially relevant text fragments from which users can extract knowledge that meets their goals.

This article presents the examples illustrating the potential and some advantages of using graph representation and deep semantic search mechanisms in the tasks of information support of cognitive processes. If the ontographic search mechanisms are adequate to the stages and features of reading/understanding the text, then we can talk about the transfer of a part of human cognitive activity to a distributed computing environment, which will be the first step towards informational cognition.

To construct the examples, we used the xIRBIS documentary information-analytical system [2] supplemented by the experimental implementation of deep semantic search mechanisms.

TEXT PERCEPTION AND GRAPHS

The process of visualization of any data is aimed at presenting them in a form that is convenient for visual observation and analysis. The visual analysis of a document graph helps to detect paths or connectivity components that are relevant to the user's search needs, and further transition from graph vertices to fragments (syntax units) of the source text and combining such fragments allow one to form new knowledge as well as check existing knowledge for consistency.

The effectiveness of visualization methods is largely ensured by the meaningful use of the principles of information perception, the adequacy of the metaphor and the visualization model. Based on the general principles of perception of visual information in relation to the problem of search on graphs, it can be assumed that: (1) the spatial and visual parameters of graphic elements can characterize the semantic similarity of fragments in the text, the frequency of use of concepts, etc. [3, 4], and managing them makes it possible to increase the efficiency of the search through the preliminary filtering and ordering of graph vertices; (2) different initial states of users and their goals

[1] Below, "graph."

(strategies) require different ways of displaying the graph and means of working with it.

According to [5], the process of graph interpretation is sequential and gradual but not holistic. This process is also significantly influenced by individual differences in the skills of understanding graphs and the prior knowledge of the semantic content of the material.

The graph of the full text of a document is usually characterized by a large power of elements (these can be thousands of names of entities (vertices) and relations (arcs) even for a relatively small text), which predetermines the need to create and use tools for selecting and displaying graph fragments that are adequate to the type and state of the problem being solved. In addition, comparing the perception of the graph and perception of the text and relying upon the models of understanding the text [6], it seems necessary to provide the graphic search tools that will allow distinguishing between mental signs, correlating them with images of reality by means of analysis and abstraction, and integrating mental signs correlated with images into the user's knowledge (i.e., to perform a synthesis).

Thus, to ensure effective use (as a replacement part in the main human activity), graph search tools must provide:

(1) selection of an array of elementary facts with their subsequent combination into a graph (operations of distinction and synthesis);

(2) reducing the dimension of the information space to a level that is acceptable to the user (abstraction operations);

(3) selection of potentially relevant concepts—reference entities (analytical operations);

(4) search on the graph and navigation through the texts of documents with the ability to pass to relevant text fragments without reading the full document, which leads to a reduction in the total time spent on the search (synthetic operations).

DEEP SEMANTIC SEARCH MECHANISMS

Any purposeful activity requires the use of information, and information must be found to be used. However, while the processes of detection and use in physical systems (and, in particular, in the brain) are almost inseparable, a generalized information system requires the development of a certain variety of interface objects and functions through which the interaction of consciousness and information systems can be implemented.

The technology for visualizing a graph built from natural language text includes the following steps:

- selection of elements of the graph in accordance with the user's task;
- display construction in accordance with the metaphor that determines the type of search task (search itself or information-analytical research);
- display visualization in accordance with the rules for the formation of visual objects and their graphic attributes.

The stage of selecting graph elements uses filters [7], divided into three groups: vertex filters, arc filters, and filters related to the graph as a whole. The vertex filters involve selection of vertices by entity name, vertex type,[2] location in the source text, term role,[3] and weight.[4] After applying the vertex filters, the graph maintains the vertices that satisfy the conditions of the filters and arcs that are incident to such vertices. The arc filters involve the selection of arcs by relation name, class,[5] modality, and location in the source text. After applying the arc filters, the graph maintains the arcs that satisfy the conditions of the filters and the vertices that are incident to them. The filters related to the graph as a whole allow one to set additional conditions for selecting vertices and arcs (for example, leave the vertices in the graph that do not satisfy the vertex filters but are included in the same connectivity component with them).

When making a search on graphs, the user can solve research or analytical problems, relying upon the absence or presence of prior knowledge of the subject area. If the user has ideas about the objects he needs (an individual concept or links between concepts), it must be possible to find and display them on the graph (use the user's knowledge when navigating the graph). The neighborhood search and path search metaphors (visualizing the corresponding mechanisms) are provided for this purpose.

In the absence of prior knowledge, the user must be given the opportunity to form a graph in the form that is most suitable both for the task being solved and for perception. For this purpose, various graph display construction mechanisms are provided that correspond to different user expectations (a certain perception scheme—metaphor): based on a gravity model, based on a hierarchy of path lengths, or based on a functional model.

The set of rules for the formation of visual objects and their graphic attributes, such as color, shape, or size, must provide a variant geometry of the formed set of arcs and vertices (calculation of their coordinates in the display space).

Next, we consider the following types of deep semantic search mechanisms defined in the article [1]:

[2] The vertex type characterizes the origin of the corresponding name: from the text, from the thesaurus, from the taxonomy of properties and units of measurement, etc.

[3] The role of the entity name is determined based on the extended functional model [8].

[4] The vertex weight is calculated based on the frequency of occurrence, role, belonging to significant text fragments.

[5] The relationship class is defined in accordance with the taxonomy of functional relationship classes [9].

(1) graph display construction[6] in accordance with the search metaphor and transformation using graph operations, including semantic scaling;

(2) filtering (according to the entity name or relationship class, aspect projection);

(3) search for the neighborhood;

(4) search for a path.

IMPLEMENTATION OF DEEP SEMANTIC SEARCH MECHANISMS

A distinctive feature of deep semantic search is the selection of fragments of documents that together meet a real information need (and not at the level of expressed information, as in classical search engines), which implies a meaningful analysis of the text at the level of statements. At the same time, the analysis is largely determined by the specifics of the semantics and pragmatics of the problem being solved, as well as the cognitive state of the user.

A set of documents that serve as preliminary material for subsequent analysis can be formed by means of classical information retrieval. For example, the xIRBIS documentary information-analytical system implements a system of models of classical search mechanisms for these purposes [10], which is complete in terms of a set of operational objects and their states.

Further, to make a deep search, documents are presented in the form of occurrence matrices of the corresponding graphs and converted into a graph structure that includes an array of vertices and an array of arcs (search results for several queries can be combined in one structure). Graph visualization provides the user with the opportunity to conduct further searches, using mainly tools for working with graph elements.

Thus, information retrieval focused on the permanent support of cognition processes can be reduced to sequential (but not necessarily strictly periodic and corresponding to a fixed scheme) selection of documents and deep semantic search itself—an automated analysis of the content of found documents using a graph.

Mechanisms for Constructing Graph Display in Accordance with the Search Metaphor

The main goal of such mechanisms is to reduce the space of perception and to arrange and format graph elements in accordance with the semantics of the document and the pragmatics of the task, thereby reducing the user's search efforts.

Depending on the user's cognitive state (whether the user imagines the ways to solve the search problem or does not have a solution image), the opportunity can be provided to apply the graph display construction mechanisms both for different placement of graph elements in the display plane and for reducing the variety of semantic relationships or enlarging concepts with the help of linguistic support (for example, thesauri or ontologies).

The following algorithm is used as the basis for the graph display construction mechanisms:

(1) selection of the set of vertices V and the set of arcs E of the graph $G(V, E)$;

(2) selection and indication of the display function $F(G(V, E), P)$, where P is some set of characteristic parameters of vertices and arcs. Such parameters can include the frequency of occurrence of the corresponding terms, their position in the text, roles, etc.;

(3) calculation of coordinates of vertices and arcs on the display plane;

(4) display of the graph on the plane.

Further, the examples of applying the mechanisms take various search situations into account, which are solved based on a set of documents previously selected on request about the problem of coolant leakage in NPP circuits.

Display Mechanism Based on a Gravity Model

Force algorithms (including the Barnes–Hut algorithm used in xIRBIS, which was formulated in terms of solving the n-body gravity problem) are based on physical analogies. Such models are based on the idea that the vertices repel each other with some force, and the arcs act as sources of attractive forces that hold the vertices that are adjacent to the arcs. The final picture of the graph will correspond to the equilibrium distribution of forces in the system of vertices and arcs. Moreover, the vertices with the least number of connections will be located in the peripheral areas of the graph, and the vertices with the largest number of connections will be located in the central areas. The result of display calculation depends on the ratio of repulsive and attractive forces, which are the parameters of the gravity model. These parameters cannot be adjusted by the user in the current implementation.

The use of such a display mechanism allows the user to focus on the contexts in which the problem is considered in the selected documents—different contexts form their own areas of attraction.

Figure 1 shows the result of displaying a graph based on a gravity model.

The size of a displayed vertex depends on the frequency of occurrence of its name in the texts of documents. As can be seen in Fig. 1, clusters are formed around peaks with a higher frequency (for example, "NPP," "NPP power unit," "Search for a coolant leak in the 1st circuit," "Accident analysis"), which make up "centers of attention." Then, the user can proceed to a detailed analysis of the graph within the selected cluster—the context.

[6] In this case, visualization tools can be considered as search tools that perform array ranking. This makes it possible to lower search efforts by reducing the space of perception, as well as ordering and formatting graph elements in accordance with the semantics of the document and the pragmatics of the task.

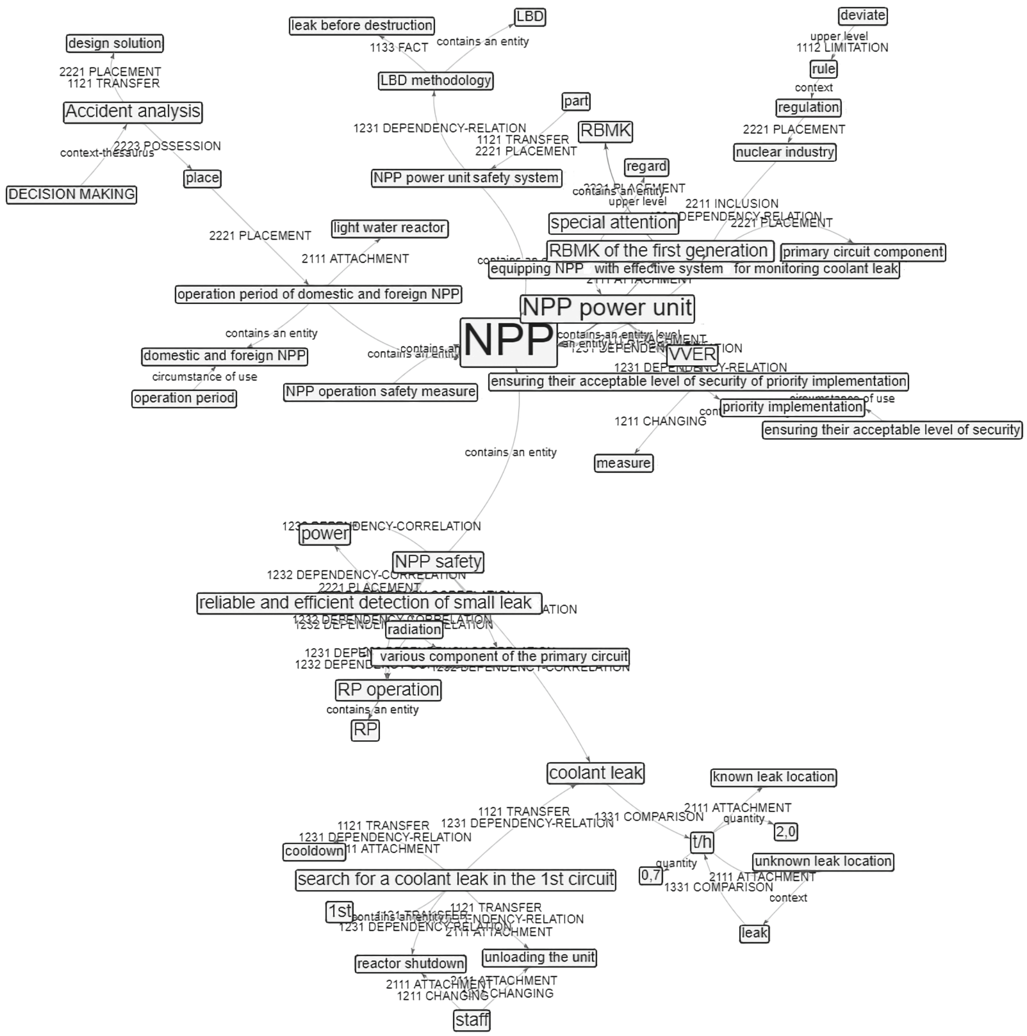

Fig. 1. Graph built using the display construction mechanism based on the gravity model (the names of vertices and arcs for all graphs are given in a word-by-word normalized form).

Thus, on the basis of significant concepts in clusters, the user gets the opportunity to form some (one might say, conceptual) idea of the content of the selected documents without reading them completely.

Display Construction Mechanism Based on a Hierarchy of Path Lengths

The purpose of the mechanism is to localize the longest chains of facts containing perhaps the greatest amount of information. Its implementation is based on the following logic: a longer path—a more accurate understanding of the context—a more accurate selection of relevant vertices—a more accurate selection of relevant fragments.

Among the parameters for constructing a display based on path lengths, the minimum allowable path length can be set, and, when calculating the path length, one can specify whether it is necessary or unnecessary to take into account the direction of the arcs connecting the vertices.

The display construction algorithm is as follows:

(1) selection of paths in the graph (in this implementation of the system—using the Floyd–Warshall algorithm) according to the criterion of exceeding the path length of a given threshold value;

(2) sorting the set of selected paths in descending order of path length;

(3) sequential arrangement of paths on the plane (assignment of coordinates to the vertices) in such a way that the longest paths will be located higher. In this case, each path is laid from left to right, based on the order of the constituent vertices, and, in addition, the vertices included in several paths are not duplicated, and the arcs that are incident to them are attached to the first sample of the vertex found (such arcs reflect the connections between the paths).

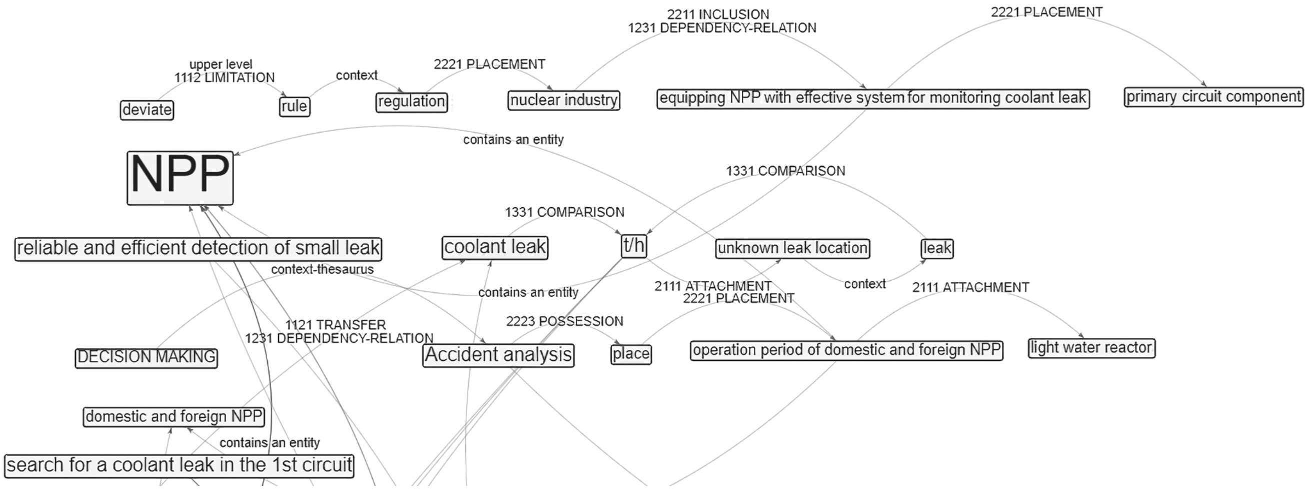

Fig. 2. Graph (fragment) built using the display construction mechanism based on the hierarchy of path lengths.

Viewing the result allows the efficiency of detection of potentially useful entities to be increased, as longer paths correspond to a greater variety of elements that form them, and, therefore, the probability of finding a useful entity in this variety is higher.

The graph built according to the documents on the problem of coolant leakage is shown in Fig. 2. The minimum length of the path in displaying is 1; only unidirectional arcs were taken into account when constructing the path.

Such a displaying manifests well not only strongly related contexts, but also the concepts that connect them.

This type of displaying can be useful in selecting key concepts, since longer paths collect most of the source text. Moreover, the user has access to both the concepts themselves and the relationships between them.

Display Construction Mechanism Based on a Functional Model

Graph vertices can be arranged by grouping them according to the roles that the corresponding concepts play in the text. The roles are determined at the stage of automatic text processing using the ontology of relationships [9]. Viewing the graphs visualized in this way can help in the case when the user wants to have an idea of a subject area (SbA) as a process within the framework of solving a problem.

The current implementation defines the following roles:

Problem (prerequisite, reason, problem);

Source (source, input data, object, subject);

Foundation (grounds);

Function (function, process);

Condition (control, factors, conditions, scope, novelty, reliability);

Tool (methods, means, conditions of use);

Result (result, task);

Target (goal, practical significance, consequence, recommendations).

The vertices for which no role is defined are marked as Undefined.

When constructing a display, the display area is divided into five parts along the horizontal axis and into three parts along the vertical axis. The vertices are located depending on the role, according to the scheme in Fig. 3.

Figure 4 shows the display of the graph according to the metaphor of the functional model for documents on the topic of coolant leakage in NPP circuits. For compactness of the image, the figure does not show the vertices with the role of Undefined.

As can be seen (see Fig. 4), the display mechanism used corresponds relatively well to the idealized functional model[7] [7]: the vertices with the role of Function are selected ("equipping NPPs with effective system for monitoring coolant leak"); the vertex "coolant leak" is assigned the role of Source; the vertices with the role of Tool are indicated ("staff," "reactor shutdown," and "unloading the unit"); the vertices "regulation," "rule," and "accident analysis" are assigned the role of Condition. The role of Problem has not been defined, so the corresponding area is not shown in Figure 4.

Further, the user has the ability to manifest and analyze contexts using the neighborhood and path search mechanisms.

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[7] Note that automatic role recognition is in the stage of formation at the moment and therefore is not always correct, but even this result allows the user to form an initial idea of the processes described in the text.

		Condition		
Problem	Source Foundation	Function	Result	Target
		Tool Undefined		

Fig. 3. Role display zones for the functional model.

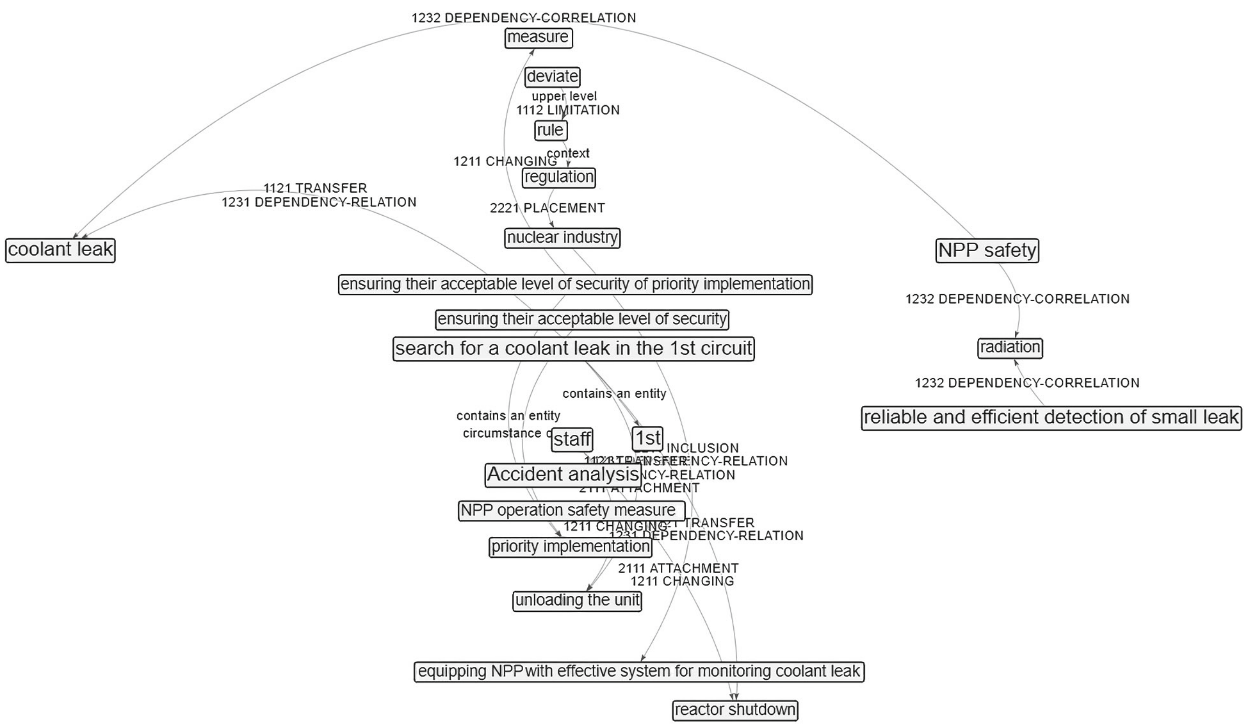

Fig. 4. Graph built using the display construction mechanism based on the functional model.

Semantic Scaling Mechanisms

In addition to the means of presenting the facts of established knowledge, information retrieval focused on the processes of cognition must have means of ordering knowledge, which makes it easier to establish cause-and-effect relationships and minimize the length of cause-and-effect chains. Semantic scaling mechanisms that provide the possibility of presenting the content of a document at various categorical levels (part-whole, particular-general, specific-abstract, etc.) have been implemented for this purpose.

The semantic scaling mechanisms include enlargement as an aggregation of objects according to the feature of occurrence (part-whole relationship) and generalization through bringing object-concepts/relationships (constituting a generalized image) to a higher level of generality (class-type relationship).

In case of semantic enlargement, the original graph hides all intermediate vertices (i.e., not initial and not final) in the chains that include only relationships from the "part-whole" class. In case of generalization, specific concepts are replaced by class ones (that is, the general properties of objects are used) with preserving the class of the original relationships.

To demonstrate semantic scaling, let us consider a text fragment that describes the purpose and composition of the main circulation pump unit:

Fig. 5. Graph built according to the text for the description of the design of the main circulation pump.

The main circulation pumping unit (MCPU) is designed for coolant circulation creation in primary loop and heat extraction from a reactor core. The MCPU has an additional function of coolant circulation ensuring on runaway in case of various accidents with blackout. An additional function allows for a smooth transition to a natural circulation mode

The pump consists of a housing and a removable part. The removable part is sealed with a trapezoidal copper gasket to ensure tightness. The housing is made of heat-resistant steel grade 48TS, protected from the inside by a stainless overlay. Support legs are welded to the housing. The support legs lean on the base frame. The removable part consists of an upper radial-axial bearing, a pump shaft, an impeller, a guide apparatus, a frame, and a cover with a neck welded from 48TC steel forgings. A mechanical shaft seal and a hydrostatic bearing are located in the neck. The pump shaft is one-piece forged and made of steel 20Kh13. The impeller with double curvature blades is welded from two parts: a disk with blades and a cover disk. The impeller and the guide apparatus are made of stainless steel 10Kh18N9TL.

The graph constructed according to this text is shown in Fig. 5. For convenience, some vertices have been moved manually.

Note that the resulting graph consists of two subgraphs, which we will refer to in the future: the subgraph on the left side of Fig. 5 corresponds to the first paragraph of the text, and the subgraph on the right side of Fig. 5 corresponds to the second one.

Semantic Enlargement Mechanism

Graph semantic enlargement is performed by identifying arcs on the graph that correspond to part—whole relationships and replacing the arc with the vertices that are incident to it by the whole vertex with preserving all other arcs of both vertices. This is how the subgraphs that are the result of dividing the whole into parts are replaced by one vertex.

Identification of relationships in constructing a graph is provided by using the classification of relationships. The upper level of this classification is represented by a combination of three facets that reflect the ratio of the separate and the aggregate (separate—separate, separate—whole, whole—whole), the reality/model ratio, as well as the form of manifestation of the relationship. Classes are encoded using a positional coding system; the first position of the code is reserved for the facet of the relationship between the separate and the aggregate. Thus, the code of the relationship class that is part of the hierarchy that grows from the top-level class with the facet focus representing the separate-whole relationship begins with number 2.

An illustration of the application of semantic enlargement is given by the example of the subgraph on the right side of Fig. 5. The result of the enlargement is shown in Fig. 6: the arcs that correspond to part—whole relationships were identified on the subgraph, and the arcs with the vertices that are incident to them were replaced by the whole vertex maintaining all other arcs of both vertices.

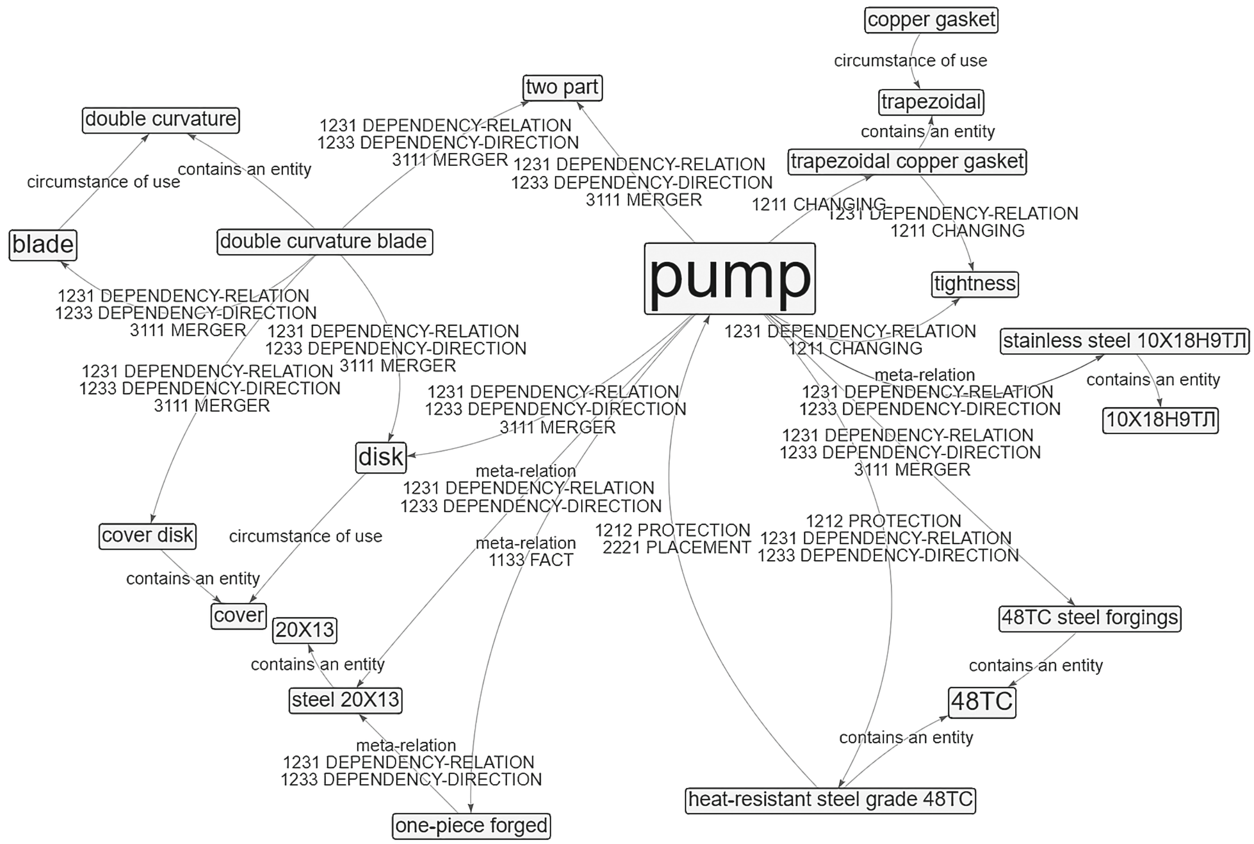

Fig. 6. Graph built using the transformation mechanism with the help of the operation of semantic enlargement (the original graph is shown in Fig. 5, on the right. The enlargement yielded the subgraph, in which all the design components of the pump were replaced with the vertex "Pump" which became the most significant in the graph).

Semantic Generalization Mechanism

The mechanism for semantic generalization of meaning content involves the replacement of context-specific entity names with thesaurus descriptors that represent concepts of a higher level of generality.

In accordance with [11], information retrieval thesauri are used in the formation of triplets based on the text; these triplets form the basis of the graph to build structural linguistic context-thesaurus relationships. Such relationships can also be observed in Fig. 5. A feature of building the relationships is to add as vertices only those thesaurus descriptors whose length (in words) is greater than 1.

Semantic generalization additionally selects thesaurus descriptors that have a minimum intersection (but not less than one word) with the terms located at the graph vertices. All descriptors selected in this way are attached to the corresponding vertices through the context-thesaurus relationship. If the thesaurus contains ascriptors and, accordingly, if they are selected, the ascriptors are replaced by their corresponding descriptors (through the ***USE*** relationship).

The next step is to find the roots of the branches of the thesaurus hierarchical trees starting from the descriptor vertices and to replace the entire branch (including the original vertex of the context-thesaurus relationship) with the root descriptor.

To illustrate the semantic generalization, let us consider the left subgraph in Fig. 5 as the original graph.

At the first step, as a result of joining thesaurus descriptors (using the IAEA INIS thesaurus [12]), we obtained the graph shown in Fig. 7.

Next, the vertex "main circulation pump unit" will be replaced by the vertex "EQUIPMENT" (because the thesaurus has a connection "PUMPS"—***BT***—"EQUIPMENT"). The vertices "coolant circulation creation" and "coolant circulation ensuring" are replaced by the "COOLANTS" vertex (there are no higher-level descriptors). The "heat extraction" vertex will be replaced by the "HEAT EXTRACTION" vertex (there are no higher-level descriptors). The "reactor core" vertex will be replaced by the "REACTOR COMPONENTS" vertex (the thesaurus has a connection "REACTOR CORES"—***BT***— "REACTOR COMPONENTS"). The vertices "runaway," "various accidents," "blackout" are replaced by one vertex "ACCIDENTS" ("RUNAWAY (REACTOR ACCIDENT)"—***BT***—"ACCIDENTS," "STATION BLACKOUT"—***BT*** —"ACCIDENTS"). The "natural circu-

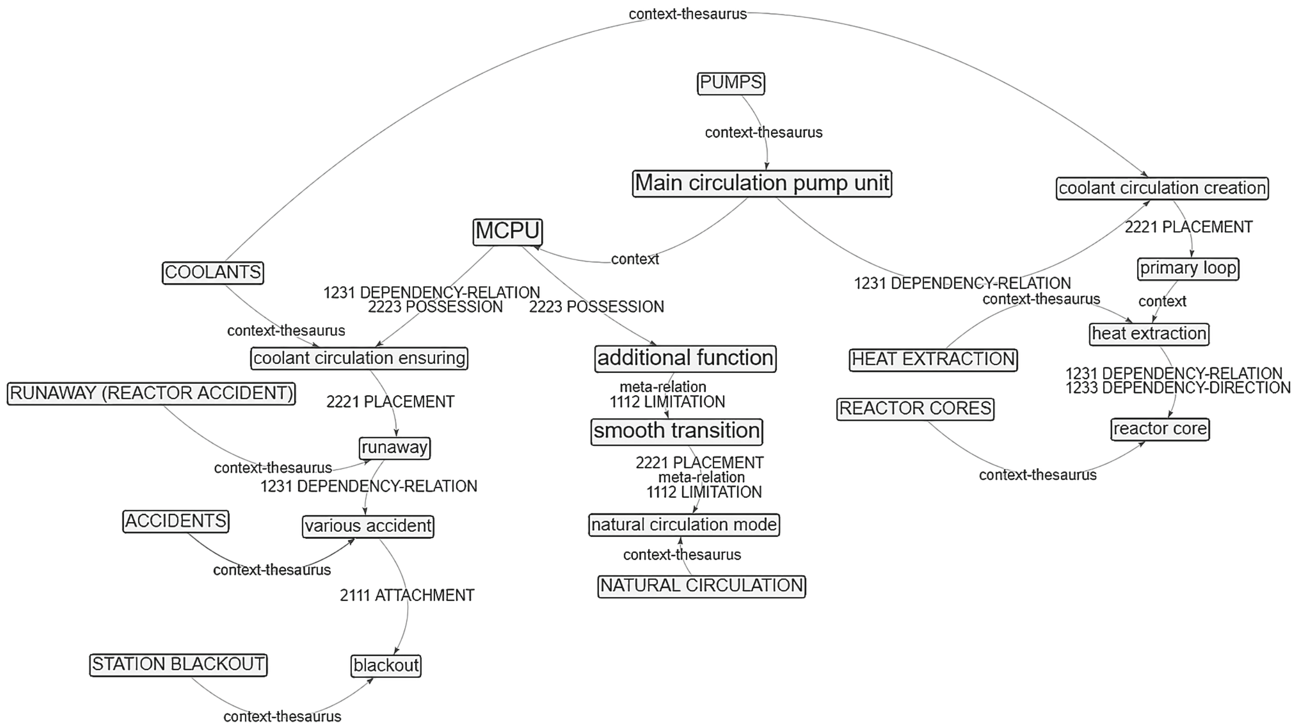

Fig. 7. Graph with attached thesaurus terms (the original graph is shown in Fig. 5, on the left. Thesaurus terms are given in upper case (except for the "MCPU" vertex)).

lation mode" vertex will be replaced by the "ENERGY TRANSFER" vertex ("NATURAL CIRCULATION"—***USE***—"NATURAL CONVECTION"—***BT***—"ENERGY TRANSFER").

The result of semantic generalization is shown in Fig. 8.

Thus, applying the operation of generalization, we pass to the concepts of a higher level of abstraction (equipment, power transmission, reactor units, etc.).

Aspect Projection Mechanism

Aspect representation, one of the forms of a complete fact that reflects a certain semantic slice of a subject area, is implemented as a subgraph. The construction of aspect representation is based on the projection operation, which is reduced in [13] to the operation of the intersection of the original and aspect ontologies (primarily at the level of graphs of functional systems). Thus, each aspect representation must have its own aspect ontology.

In general, use is made of aspect taxonomy, which (being an object that is open to extension and modification) defines a set of possible aspects related to the relationship classes that are specific to this point of view. The set of aspects is determined in accordance with the activity model and is set based on the taxonomy of functional relationships [9].

To illustrate the application of the aspect projection mechanism, let us consider the subgraph located on the right side of Fig. 5, where, for example, the design features of the main circulation pump unit can be identified through the use of the aspect projection "Composition (Separate—Whole)" (the aspect is given by relationships, the code of which begins with number 2). The result of the operation of the aspect projection mechanism is presented in Fig. 9.

The use of projection reduces the number of displayed vertices, making it easier to perceive the graph without losing the meaning of describing the pump as the set of elements that make it up.

Neighborhood Search Mechanism

The mechanism for searching the neighborhood of the vertex enables the user to present elementary facts extracted from the text, in which the entity corresponding to the vertex participates. Its consistent application allows one to choose the next peak for visual analysis and thus form the area of research.

The user can select a vertex that is of interest to him on the graph and build its neighborhood of a given radius. If the neighborhood of the selected vertex did not participate in the formation of the original graph, then the neighborhood search mechanism is launched in the entire information array (outside the documents that formed the original graph), and the neighborhood

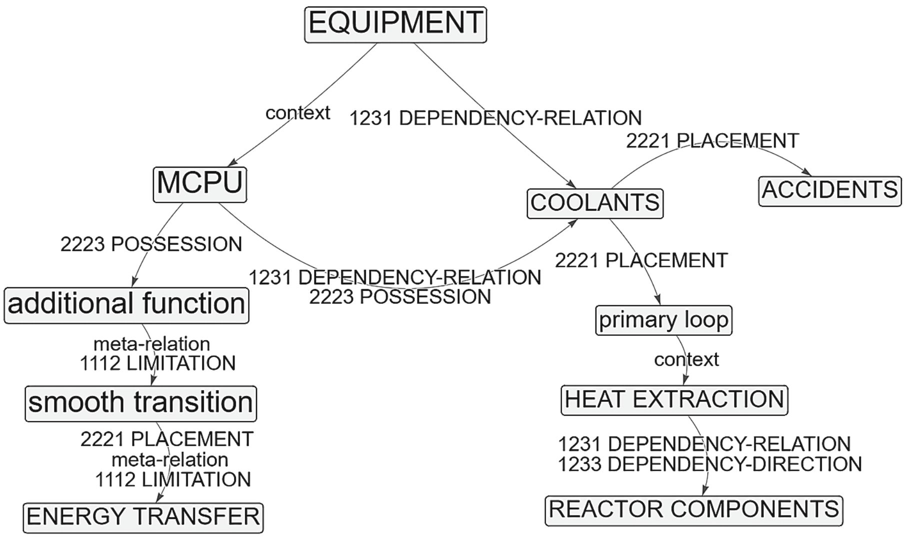

Fig. 8. Graph built using the transformation mechanism with the help of the operation of semantic generalization (the original graph is shown in Fig. 5, on the left. Thesaurus terms are given in upper case (except for the “MCPU” vertex)).

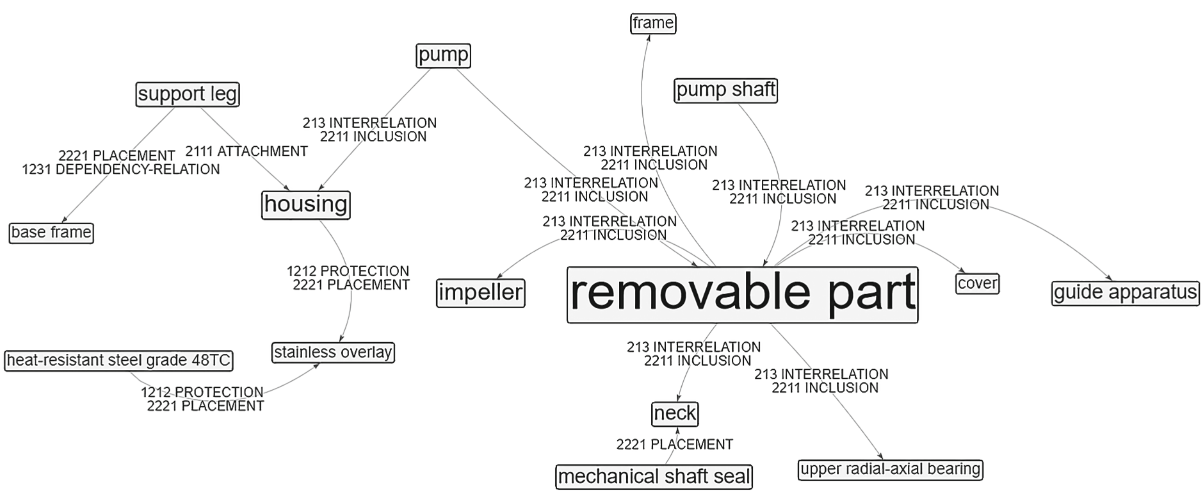

Fig. 9. Graph built using the transformation mechanism with the help of the aspect projection operation (the original graph is shown in Fig. 5, on the left).

is formed as a result of the search (it replenishes the original graph).

In the general case, the use of the neighborhood search mechanism is carried out according to the following algorithm:

(1) selection of graph vertices by a given entity name and formation of a subgraph containing vertices $\{v_1, \ldots, v_n\}$;

(2) construction of a neighborhood of some vertex $v_i \in \{v_1, \ldots, v_n\}$ and formation of a subgraph consisting of vertices $\{v_1, \ldots, v_n\}$ and vertices $\{v_{n+1}, \ldots, v_m\}$ connected with vertex v_i in some neighborhood (the radius of the neighborhood is determined by the user);

3) execution of item 2 of the algorithm for any other vertex from the set $\{v_1, \ldots, v_n, v_{n+1}, \ldots, v_m\}$;

(4) user’s visual analysis and indication of semantically significant vertices for further transition from the indicated vertices to the corresponding text fragments. Quotations are formed from the text fragments for a possible solution to the search problem.

For example, the user may select the MCPU vertex in the graph using the vertex filtering mechanism and starts the mechanism of searching for the neighborhood of radius 1. This will yield the subgraph containing the original vertex and those that are adjacent to it (Fig. 10).

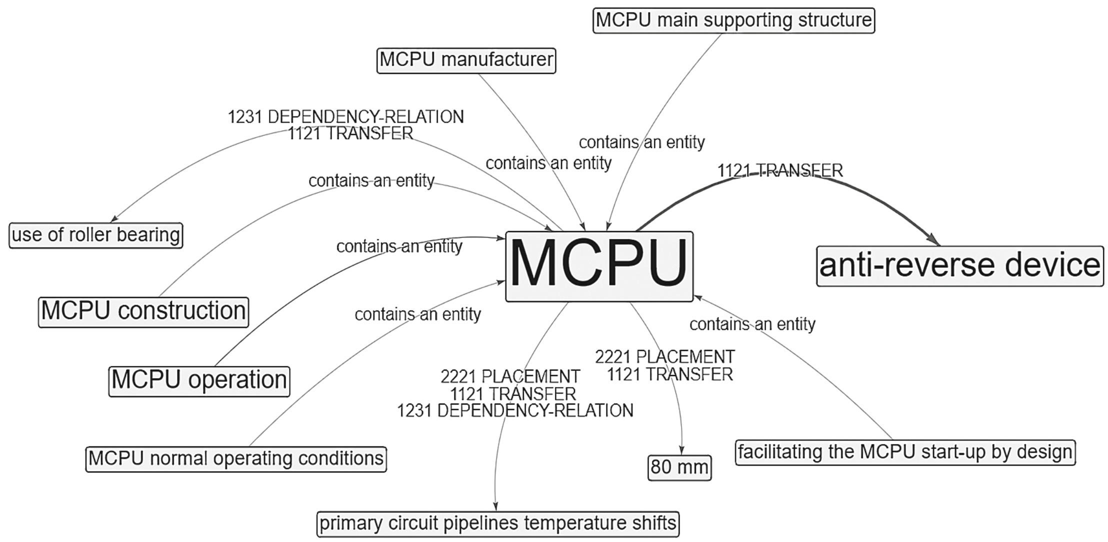

Fig. 10. Graph built using the neighborhood search mechanism for the "MCPU" vertex.

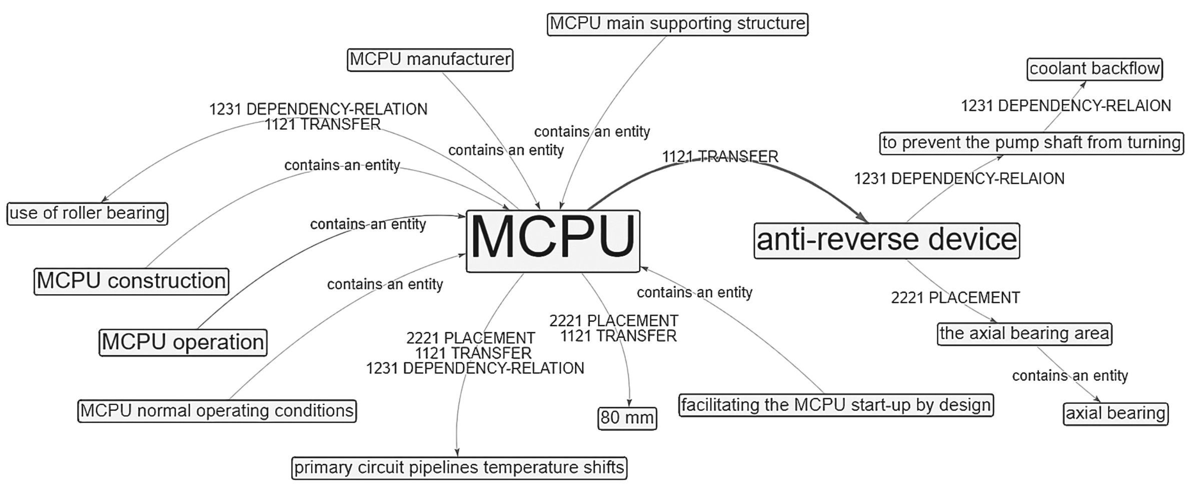

Fig. 11. Graph built using the neighborhood search mechanism for the "MCPU" vertex. The expansion of the neighborhood goes in the direction of the vertex for the anti-reverse device.

Taking into account the general task of the study or based on visual markers (for example, the size of the vertex), the user passes to the anti-reverse device vertex and reveals the neighborhood of this vertex (for example, radius 2). This will yield the subgraph shown in Fig. 11.

Thus, by revealing the neighborhood of the MCPU vertex, the user receives the data that the MCPU is equipped with an anti-reverse device located in the region of the axial bearing and serving to prevent the pump shaft from rotating. Further analysis of the semantic neighborhood suggests that the coolant counterflow can cause the pump shaft to rotate, i.e., it can lead to a violation of the coolant circulation mode in the circuit.

Path Search Mechanism

The task of finding the solution itself in the main activity can be represented as a directed process (from initial positions to the answer). Such tasks are solved using a suitable path search metaphor, which involves building a sequence of objects and actions expressed in concepts (more precisely, chains of elementary facts) from the initial entities to those corresponding to the potential solution of the main activity task.

The path search mechanism is carried out according to the following algorithm:

(1) selection of graph vertices by a given entity name (it may correspond to the search query expression) and formation of a subset of vertices $\{v_1, \ldots, v_n\}$, which must be included by the path;

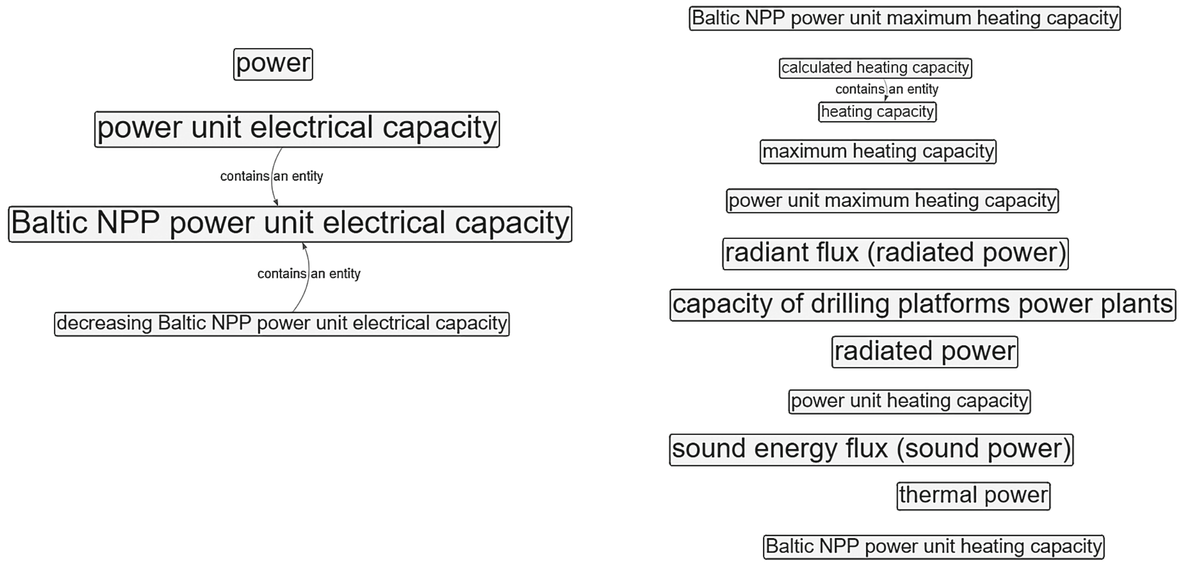

Fig. 12. Graph built using the mechanism of filtering by the entity name. The vertices containing the term *power* in the entity name were selected.

(2) selection of the shortest path containing a subset of vertices $\{v_1, \ldots, v_n\}$ in the graph (in the implementation under consideration, Dijkstra's algorithm is used);

(3) visual selection of the path (by increasing the thickness of the arcs between the vertices in the selected path or changing their color).

Next, the user conducts a visual analysis and assessment of the correspondence of the related triplet facts in the selected path to the image of the solution or the search task that he has.

Let us consider the application of the path search mechanism using the example of the problem of incomplete demand for electric capacities of the Baltic NPP under construction. Based on the understanding of the problem situation (it is necessary to find a solution to reduce the power generated by the NPP), the user indicates the concept *power* in the graph built according to the selected documents as a request for the vertex filtering mechanism. The filtering result is shown in Fig. 12.

The vertices "thermal power," "heating capacity," and similar are not considered by the user as potentially significant, since they do not correspond to the original problem of finding a solution to reduce electric power.

The vertices located on the left side of Fig. 12 are the most promising in the context of this problematic situation. To establish the context of their use, the display of the neighborhood of these vertices is initiated (Fig. 13).

Visual analysis shows that the vertex "decreasing Baltic NPP power unit electrical capacity" has adjacent vertices "steam pressure" and "excess reactivity absorption," i.e., as a result of analyzing the neighborhood, the user can assume that these are the physical parameters and processes associated with a decrease in the electric capacity of the Baltic NPP power units.

Since the ultimate goal is to form a holistic image of the solution represented on the graph as a connected path (chain of facts), the user needs to establish how the physical processes (excess reactivity absorption and steam pressure) are related to power. To establish possible relationships between the vertices "Power," "steam pressure," and "excess reactivity absorption" and their nature, the user initiates the construction of a path (using the appropriate mechanism) for these vertices. The resulting graph is shown in Fig. 14 (the path is marked with a thick line).

Reading the entire path suggests that an increase in steam pressure in the steam generator will lead to a decrease in the temperature difference of the steam generator, as a result of which the average coolant temperature will change leading to the formation of excess reactivity. The absorption of excess reactivity will lead to a decrease in the electric capacity of the Baltic NPP power unit.

Thus, a relationship was found between the parameters of steam pressure in the steam generator and the electric capacity of the power unit, and the nature of the relationship was established—an increase in pressure will lead to a decrease in power.

EXPERIMENTAL EVALUATION OF THE EFFICIENCY OF GRAPH SEARCH MECHANISMS

To determine the efficiency of using a graph as a tool for navigating through text and vertices, we will conduct an experimental assessment by comparing the

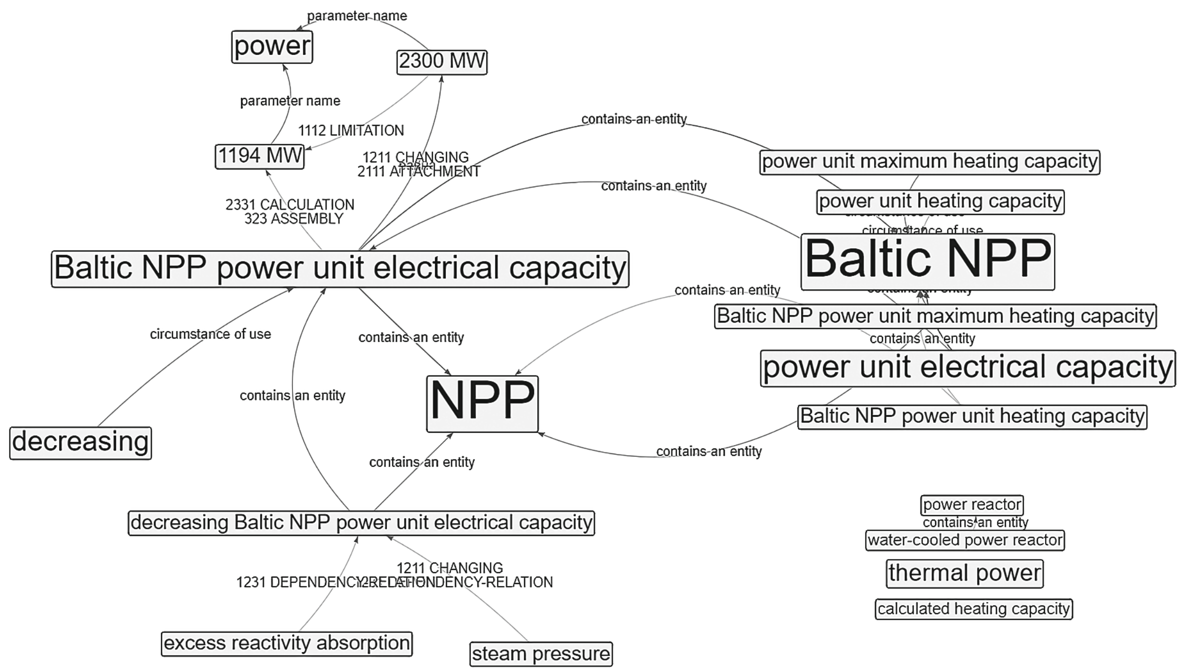

Fig. 13. Graph built using the neighborhood search mechanism for potentially relevant vertices containing the term *power* in the entity name.

volume of the original text and the volume of fragments obtained as a result of using the mechanism for constructing a path between the vertices of the graph built from the text.

Based on the fact that reading does not necessarily come down to sequential processing of text symbols [14] and that human consciousness is characterized by physical (physiological) limitations in terms of processing information in working memory (the number of objects of attention in the process of perception-understanding is limited to few units according to the Miller principle [15]), let us consider the following scenarios of passing through the search results presented in graph and text form.

The optimistic scenario. The user's attention is focused on a graph element (vertex or arc), the transition from which to text fragments immediately allows one to get a solution to the problem. In this case, the user only needs to read the element's label and the corresponding text fragment. The scenario corresponds to the lower estimate of the complexity.

The realistic scenario. To construct a solution to the search problem, a path is built on the graph between two vertices containing reference concepts. After reading the labels of the graph elements belonging to the path, the user navigates to the corresponding fragments of the source text and reads them.

In this scenario, the user is forced to read all the labels on the path elements and the entire fragment that corresponds to the selected path.

The pessimistic scenario. After constructing the path, the user sequentially proceeds to a text fragment from each graph vertex on the path, each time rereading all previously received fragments anew. The scenario corresponds to the upper estimate of the complexity.

In this scenario, the fragment corresponding to the last vertex of the path will be read once, and the fragment corresponding to the first vertex will be read as many times as there are vertices in the constructed path.

We will assume that the labor costs for the formation of a solution to the problem of the main activity (as the equivalent of efficiency) are proportional to the number of words read by the user. To make a comparative assessment of the effectiveness of using a graph as a text navigation tool, we will compare the number of objects (words, names) read when working with the graph with the number of words in the source text.

As part of the experiment, the following hypothesis will be tested: navigating through the text using the graph (according to various scenarios) can reduce the labor costs for reading and understanding the text due to a controlled reduction in the number of objects in the focus of attention. It is assumed that the use of the graph will allow cutting off text fragments that are irrelevant to the current task, focusing the user's attention on the concepts that are characteristic of his problem situation.

Labor costs are estimated according to the following indicators:

$$a_1 = \frac{w_2 + \dfrac{w_1}{2v_1 - 1}}{w_0} \text{ for the optimistic scenario;}$$

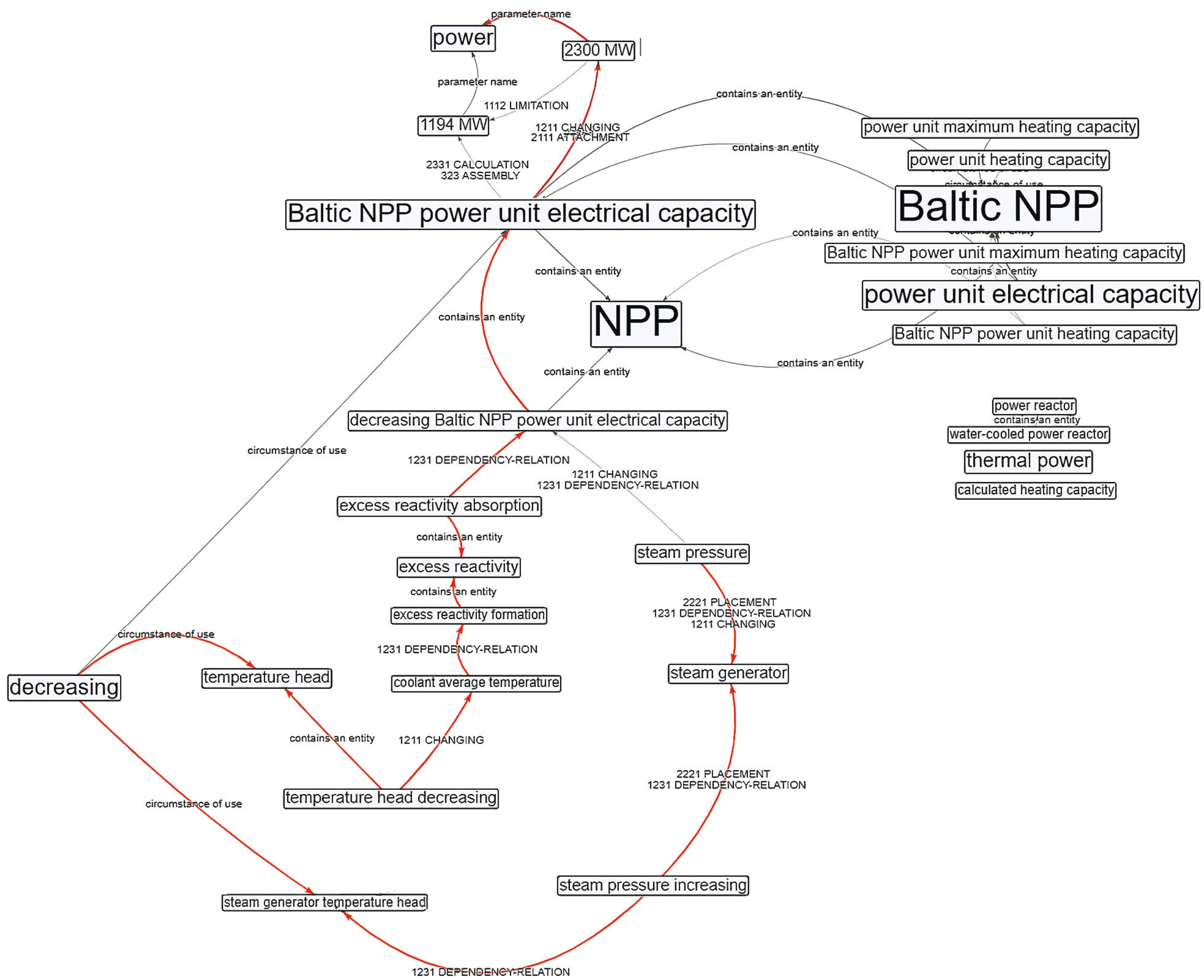

Fig. 14. Graph built using the path search mechanism between the vertices "Power," "steam pressure," and "excess reactivity absorption."

$$a_2 = \frac{w_2 v_2 + w_1}{w_0} \text{ for the realistic scenario;}$$

$$a_3 = \frac{w_2 \dfrac{v_1(v_1+1)}{2} + w_1}{w_0} \text{ for the pessimistic scenario,}$$

where w_0 is the number of words in the source text;

v_1 is the number of unique vertices in the path built on the graph;

w_1 is the number of words in vertex labels and arc labels in the path built on the graph;

w_2 is the average number of words in sentences in the source text.

We will assume that the reciprocal of labor costs ($1/a_1$, $1/a_2$, $1/a_3$) is proportional to the search efficiency.

As experimental data, we used fragments of texts of different types (Table 1): design documents (texts No. 1, No. 2, No. 3) and operational documents (texts No. 4, No. 8, No. 9), scientific articles (text No. 5), as well as fragments of literary texts (texts No. 6, No. 7).

Table 2 shows the calculated indicators for assessing labor costs and the efficiency of applying the ontology graph for texts given in Table 1.

The results of the experiment show that the use of a graph as a tool for navigating through the text makes it possible to reduce the labor costs for reading and understanding the text, as evidenced by the fact that the indicators a_1, a_2, and a_3 have values less than one.

It also follows from the calculated indicators that the use of the graph for texts of small volume (two to three sentences) does not reduce labor costs in comparison with reading the original text and in some cases significantly increases them. However, search efficiency for large texts (more than a thousand words) increases by 8–9 times due to the use of the ontology

Table 1. Particular indicators of document representations (text, graph, and path)

No.	Text document	Indicators			
		w_0	v_1	w_1	w_2
1	MCPU description	45	6	19	15
2	Steel grades	108	5	11	17
3	MCPU design	181	8	25	9
4	The problem of lack of demand for NPP capacities	195	7	46	14
5	Semantic shift	323	9	25	17
6	"Hedgehog" by M.M. Prishvin	606	7	14	16
7	"Malefactor" by A.P. Chekhov	1062	7	14	15
8	Water leakage in the first circuit of the reactor	1124	6	25	19
9	Problems of increasing NPP maneuverability	1792	10	38	19

Table 2. Relative labor costs

No.	Text document	Indicators					
		a_1	a_2	a_3	$\frac{1}{a_1}$	$\frac{1}{a_2}$	$\frac{1}{a_2}$
1	MCPU description	0.37	2.42	7.42	2.69	0.41	0.13
2	Steel grades	0.17	0.89	2.46	5.93	1.13	0.41
3	MCPU design	0.06	0.54	1.93	16.97	1.87	0.52
4	The problem of lack of demand for NPP capacities	0.09	0.74	2.25	11.12	1.35	0.45
5	Semantic shift	0.06	0.55	2.45	17.49	1.81	0.41
6	"Hedgehog" by M.M. Prishvin	0.03	0.21	0.76	35.49	4.81	1.31
7	"Malefactor" by A.P. Chekhov	0.02	0.11	0.41	66.06	8.92	2.45
8	Water leakage in the first circuit of the reactor	0.02	0.12	0.38	52.84	8.09	2.65
9	Problems of increasing NPP maneuverability	0.01	0.13	0.60	85.33	7.86	1.65

graph (compared to reading a full document) (the efficiency indicator for the realistic scenario is $1/a_2$).

Note that the above estimates do not take into account the process of constructing (search) for a path on the graph, and therefore they are obviously overestimated, but nevertheless reflect the general trend.

CONCLUSIONS

Information retrieval is always conditioned by the presence of some problematic situation, uncertainty or contradiction in knowledge that hinders the implementation of activities. The problematic situation itself sets the significance—an additional context within which the recognition and selection of reference entities for the search take place. At the same time, the mechanisms for constructing the display and transformation of graphs can play the role of a metaphor in the processes of bringing the graph to the cognitive state of the subject, forming the necessary context within which the graph elements that are relevant to the task are recognized. Interacting with the graph, the user constructs a mental image both from the elements (concepts and relationships) presented in the operational space (and in this case visual space) and from the elements of available knowledge. Moreover, it is essential that the design itself is ordered: it explicitly or implicitly follows a certain scheme of assembly, which corresponds both with the cognitive state and with the peculiarities of the user's perception.

An important feature of the search situation of deep semantic search is that the criterion for selecting an entity or relationship cannot be reduced to a single static monosyllabic expression of a threshold type (as in the case of classical search mechanisms). The relevant decision is also based on how the use of these entities/relationships will make the achievement of the goal closer.

The mechanisms of display, transformation, and search in graphs considered in this paper allow the user to interact with the system at the next stages of deep search.

(1) Selection of fragments—an array of facts for subsequent analysis performed with the help of both

classical mechanisms using inverted forms and scanning (direct organization of information)—involves mechanisms of transformation using operations on graphs (unification and intersection of graphs, semantic scaling on a graph).

(2) Selection of starting and/or supporting entities using the display construction mechanisms, which provide a convenient recognition of relevant graph elements through the use of a metaphor corresponding to the cognitive state of the subject. This stage includes filtering mechanisms and semantic scaling.

(3) Selection of relationships and entities by situationally determined features to build a path/neighborhood/text that represents a target meaning, for example, in the form of an ontology graph of a given specific situation. This stage includes the mechanisms for finding a neighborhood and finding a path on a graph.

The variety of considered deep semantic search mechanisms allows users to choose the representation of the graph that will be best perceived by them (in the context of his current task and the degree of its understanding) and used.

The transition from reading full documents to working with graphs makes it possible to use a graphically driven expert search navigation technology such as object visualization, which, on the one hand, focuses attention and, on the other hand, increases and orders the variety of entry points, including by improving visibility of key aspects of the document.

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COMPLIANCE WITH ETHICAL STANDARDS

The authors declare that they have no conflict of interest.

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