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Core Ontology for Describing Production Equipment According to Intelligent Production

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Abstract: This article presents the development of a core ontology for describing knowledge about the technological and technical parts of a production plant, in particular, theoretical knowledge for monitoring, diagnosing and forecasting of production equipment, taking into account the concept of Industry 4.0. This study is related to the definition of terms and their relationships for the processing industry in the core ontology. The core ontology is the basis for the development of domain and application ontologies, which create conditions for the system solution for the complex problems of operating industrial equipment. It consists of an ontological classification of core concepts according to the fundamental basic formal ontology. The essences of BFO were specified and revealed by methods of decomposition and generalization according to generally accepted structures of industrial enterprises. The proposed ontology contains 33 classes, 7 object properties and 34 individuals. The ontology is conceptually transparent and semantically clear, so it is suitable for theoretical knowledge transfer, sharing and retrieval. The ontology is implemented in the OWL language and validated. This article provides examples of requests for work with ontology, which prove the effectiveness of its use in industrial enterprises.

Keywords: ontology; smart manufacture; Industry 4.0; core; domain; failure

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1. Introduction

Industry 4.0 forms a new philosophy of production. Physical and virtual components are combined in cyber–physical systems [1], interacting with each other through the Internet of Things (IoT), Industrial IoT (IIoT), and cloud technologies. Reference study [2] performed analyses and made estimates regarding how integrating Internet of Things-based decision support systems along with production processes facilitates automatic data gathering and inspection of industrial plants networks in real time.

Cyber–physical systems are the foundation of smart manufacturing. Smart manufacturing offers tremendous promise. It includes everything from collecting data from sensors to complex algorithms for analysis. One of its prospective components is the ability to predict: general production trends, anticipation of possible downtime and early detection and elimination of possible causes, early detection of possible equipment breakdowns and corresponding preventive maintenance. Corresponding software implementations will allow the performance of specified operations of any complexity within smart manufacturing in real time. Another basis for the creation and successful functioning of smart manufacturing is the digital twin. The digital twin is a reflection of physical objects and virtual models [3]. Reference study [4] performed analyses and made estimates regarding the robust designs and performance of wireless sensor network-based smart systems.

To date, there is no single developed approach to most of these concepts, and the relationship between them in the context of Industry 4.0, so there are a number of areas that are developing in parallel and sometimes there are certain inconsistencies. This applies both to methodological approaches and individual implementation developments, as well as to international industry standards. However, all of this does not have a significant impact on the overall direction of development. Reference study [5] used and replicated data from BCG, BDO, Capgemini, Management Events, PAC, and PwC, and performed analyses and made estimates regarding production network performance.

A new approach to the organization of production leads to the intellectualization of all its stages and the introduction of the latest methods for collecting, storing and processing industrial information. Research study [6] performed analyses and made estimates regarding intelligent remote equipment control and optimization of the manufacturing processes through autonomous robotic systems and predictive maintenance. The use of IIoT and cloud technologies makes it possible to obtain objective and accurate data on the state of equipment and production. Research study [7] performed analyses and made estimates regarding public acceptance of and intention to use self-driving cars. Working with large arrays of heterogeneous unstructured data is no longer an extreme problem, because ontologies, cloud technologies, developed methods for working with big data and the use of appropriate digital twinning ensures the rapid development of management decisions [8]. On the basis of digital twins, it is possible to perform semi-physical modeling, which allows the simulation of scenarios of the passage of various processes in the enterprise. The result will be the identification of bottlenecks, failure scenarios, prediction of errors, equipment breakdowns, downtime, etc. In [9] there is a detailed overview of the design of a smart manufacturing system based on digital twinning.

Smart manufacture harmoniously combines, controls and regulates the interaction of the following technologies: IIoT, RAD (rapid application development), AI (artificial intelligence), edge computing, cloud, digital twin with MOM (manufacturing operations management) functions, and thus ensures the increased efficiency of advanced enterprises.

The objective of this paper is to build a core ontology for the conceptual model of the state of equipment (control equipment, electrotechnical equipment) [10], which is part of the implementation of smart manufacturing, with the digital twin as the equipment (asset) [11].

The formal model of a four-level ontology can be represented as a quartet:

$$O = < OBFO, OCore, \{ODom\}, \{OAp\} > \tag{1}$$

where OBFO—op-level ontology, OCore—Core ontology; {ODom}—Domain Ontology set; {OAp}—Application ontology set.

The following tasks must be accomplished in order to achieve the objectives:

- To develop a core ontology that is focused on a particular type of production, includes generalized classes of processes and equipment, and is designed according to a standardized hierarchy;
- To verify the quality of the created ontology according to generally accepted criteria and based on the evaluation of the complexity and formality of the structure at the vocabulary level, taxonomy level, and non-taxonomy level.

The issue of integration of top-level, core, domain and applications of ontology is not considered within this paper. In addition, this paper considers the part of ontology devoted to identifying equipment breaks and their locations. The work has been done in Protege. Protege is OWL-compatible and allows the integration of existing and developed ontologies [12].

2. Place and Role of the Subject Domain Ontology in the Ontological System of Production

The properties of smart manufacture as a complex system are uniqueness, weak structuring, many heterogeneous systems/subsystems, many heterogeneous elements, modular structure, so the design, development and implementation processes are quite complex. Therefore, the basis of a smart manufacture information system can be knowledge and the tools to work with that knowledge. The Reference Architecture Model for Industry 4.0 (RAMI 4.0), which is a 3D map of Industry 4.0 solutions [13] or a similar concept of intelligent manufacturing system architecture (IMSA), Scandinavian Smart Industry, should guide smart manufacturing development. RAMI 4.0 provides a focus on matching parts of smart manufacturing being created, in sectors. Each RAMI 4.0 sector, in turn, ensures compliance with national and international standards. Completing all of the cells in the models above ensures that smart manufacturing is as complete as possible. The disadvantage is the problematic nature of linking the cells together into a single, continuously functioning system because they are filled with heterogeneous, unstructured information.

One of the most comprehensive models describing the structure of smart manufacture in accordance with international standards is SSIF [14]. The authors have developed a number of approaches corresponding to the multiple cells of this model. In particular, an approach for diagnostics and forecasting of control system (regulated part) [15] has been developed; a scenario–cognitive approach [16] has been developed for effective use of equipment. To analyze and predict the occurrence of a process disorder, an approach based on a combination of the scenario–target approach and statistical control has been developed in [17,18]. However, again there is a problem of logical connection of the results of solving these problems with each other.

To date, there is one approach to combining practical and fundamental knowledge used in solving specific problems in industry. This is the use of ontologies. Applied work [19] on the development of a production information system for a dairy plant, which uses a multi-level ontology OSTIS and international standards, is known. However, limiting only the information component of the enterprise significantly narrows the possibilities of the ontology. The only way to connect IIoT, cloud, digital twin, cyber–physical systems in smart manufacture, etc., which corresponds to certain cells in the RAMI 4.0 model, within the concept of Industry 4.0 is to create an ontology. Significant advantages of the ontological approach in this case are their purpose—to work with heterogeneous unstructured information. During development of a set of cells of any production metamodel from the point of view of a system analysis it is required to use a uniform meta-ontology and corresponding hierarchy. Such ontologies are top-level ontologies: basic formal ontology (BFO) [20], DOLCHE, SUMO, GFO. For the successful functioning of smart manufacturing and combining its components—digital twin, IIoT, cloud— the information in the ontology must be presented at different levels of abstraction with varying degrees of detail. This will reduce the time it takes to perform various operations and procedures.

In the literature there is a fairly large variety of works on the construction of ontologies of different levels for different subject areas, which indicates the relevance of this direction. There is a branch of works devoted to the development of industrial ontologies, which serve as a basis for the intellectualization and digitalization of manufacturing enterprises.

The actual problem of effective operation of an enterprise, taking into account the concept of smart manufacture, is how to ensure uninterrupted operation of production at all levels. The problems affecting the quality and efficiency of production processes can be conditionally divided into two groups. The first group is technological problems caused by a variety of internal and external influences on the technological component. The result is disruption of the technological process, transient processes of regulated technological variables outside the permissible limits, deterioration of the quality of the semi-product and the final product, increased intermediate losses, occurrence of pre-emergency and emergency situations, decrease in output, increase in costs, loss of energy and resource efficiency. The second group is the problems of technical character caused by various breakdowns of technical means, technological, electrotechnical and control equipment. The result is a shortage of products, deterioration of the quality of the final product, and downtime associated with unplanned repair work of varying complexity.

The technical literature [21] proposes a context model for industry based on Industry 4.0 concepts. The context ontology is implemented at three levels: the top, core and three domain ontologies: sensor ontology, location ontology, and time ontology. Its peculiarity is that it is aimed at contextualizing individual concepts of production assets, describes only the organizational and production structure of production, but it cannot be used for typical industry tasks, in particular diagnostics.

Among the works devoted to the development of breakdown ontologies, it should be noted that [22] gives one of the first breakdown classifications and creation of a diagnostic system to determine the location and cause of breakdowns of different complexity and depth for turbine operation control. Another work [23] on domain ontology references the diagnostic system of steam turbine operation. It is reasonable to build ontologies to determine the breakdowns of electrical equipment. In [24], the ontological approach to diagnostics of malfunctions of electric networks is investigated, and in [25] an ontological approach to diagnostics of malfunctions of transformers is offered.

Diagnostic ontology systems are also being developed in the field of information component breakdown finding. They can be aimed at troubleshooting for industrial control applications [26] or detecting SCADA system failures due to external interventions [27].

Consequently, the issue of diagnosing equipment breakdowns in manufacturing enterprises on the basis of ontologies is rather poorly developed, and taking into account the concepts of Industry 4.0 is in its early stages. There is also no single unified concept for diagnosing the state of pieces of equipment.

Building a domain ontology for monitoring technical means of industrial enterprise for smart manufacture based on Industry 4.0 concepts is relevant. The implementation of this system will significantly reduce the time to search for breakdowns, reduce downtime, increase revenues, ensure resource and energy efficiency of the enterprise, which is the most important problem today [28].

3. Materials and Methods

To solve the problem, it is necessary to design a multi-level ontology, which will disclose the conceived concept. There is a certain set of hierarchy ontologies, which have their advantages and disadvantages. To achieve the objective, the authors chose a four-level ontology, shown in Figure 1. It is based on the classical three-level ontology of Guarino [29] with the addition of another core level. This choice provides a conceptually correct solution to the problem. The chosen four-level ontology contains: top-level ontology, core, domain ontology, application ontology (Figure 1).

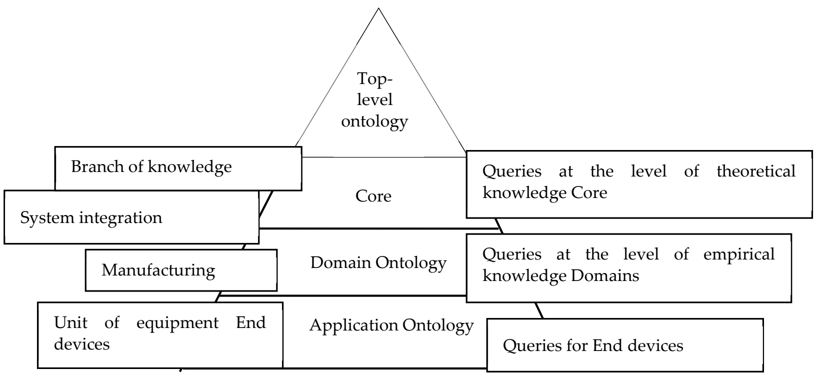

Figure 1. Four-level hierarchy of ontology.

Each level of the hierarchy of ontology performs its functions, which ensures the development of high-quality conceptual models to represent the context of the subject area and its management. The overall objective of the paper is to systematize the theoretical knowledge and basic concepts of industrial enterprise in the form of core ontology, developed in accordance with the fundamental concept of BFO.

The peculiarity of modern industrial ontologies is their focus on solving industrial problems. The article presents the results of the core ontology level development to determine the breakdowns typical for a unified piece of equipment, their locations, and the causes of occurrence in order to develop proactive actions.

The developed industrial multilevel ontology contains a lot of heterogeneous static and dynamic information. Static information includes: description of industrial assets, methods of diagnosing the occurrence of equipment failures, expert information on the various characteristic types of failures and the main reasons for their occurrence. Dynamic information includes: equipment location and functions performed. The data collected from the equipment must be presented explicitly. The result of processing is information about their activities and state. The use of temporal relations between activities and spatial relations between assets and their location on the production in the ontology allows the simplification of algorithms for identifying the situation and the state of equipment. When designing the ontology, the authors focused on providing two main criteria: the possibility to reuse the modules of the conceptual model and the possibility to expand it.

The top-level ontology is the fundamental basis for the construction of lower-level ontologies, because it provides definitions and terms common to all domains. That is, in fact, it provides a single consistent definition of terms for all subject areas [30]. Concretization and contextualization of each domain is done at the lower levels.

BFO was chosen as the top-level ontology for several reasons:

1. BFO is popular—hundreds of ontologies claim to use it as a top-level ontology;
2. It has a limited number of classes (terms), which is an advantage of top-level ontology. This indicates that it is understandable and easy to work with;
3. It includes definition of higher-level concepts only, which makes it universally applicable to any subject area;
4. It combines static and dynamic (temporal) parts in its composition;
5. It is in the process of standardization;
6. It is OWL-compatible.

Figure 2 shows the implementation of a fragment of BFO (individual classes and their hierarchy), which is necessary to solve the task in Protege.

At the second level, the core ontology was constructed. It represents a higher level of generic terms to cover and provide a definition for the broader domain. Its special feature is that it is related to the domain ontology and can be the result of several domain ontologies. Using a core ontology allows us to systematize the concept for domain ontology because it is a key prerequisite for it. Since the core combines a top-level and a domain-level ontology, its proper formation ensures that the latter is understandable and collision-free and prevents the redefinition of terms. In addition, it is possible to extend the ontology by adding derived or related domain ontologies. Problems with their integration will not arise because of the operation of similar terms, the use of similar structures and relations.

The core level in the developed ontology is located between the top-level BFO ontology and the domain ontology, specifying its classes for the domain under study. The hierarchy is represented in Figure 3, containing the BFO classes, which are extended by subclasses that are core ontology level classes. Each core ontology class has corresponding instances that specify the corresponding concept and are classes for the domain ontology.

For example, the BFO class is Object Aggregate. At the core level, it is refined by the general class—Equipment (Figure 3), which in turn includes instances: Control Equipment, Electrical Equipment, and Technological Equipment, as these types of equipment are specific to production. The Technological Equipment class combines different types of technological equipment, typical for the food industry. The Control Equipment class combines different types of equipment for building automated production control systems.

The Electrical Equipment class contains different types of electrical equipment installed in production.

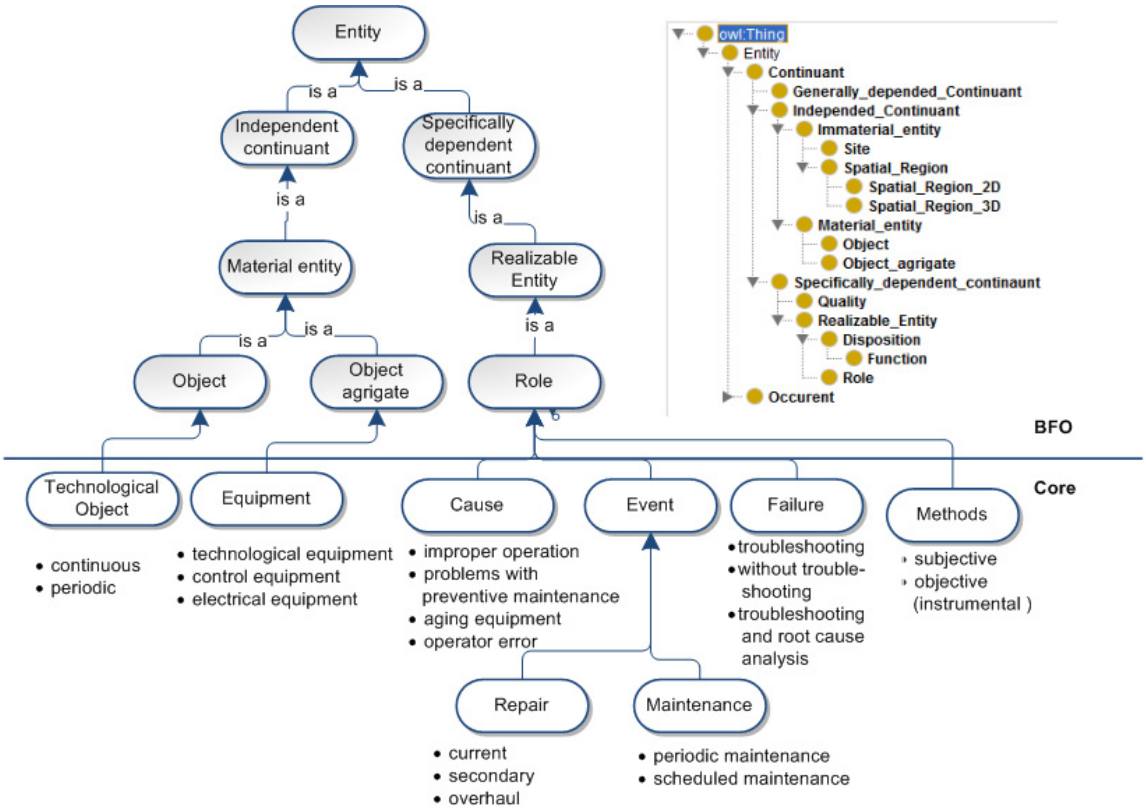

Figure 2. Fragment of BFO and core.

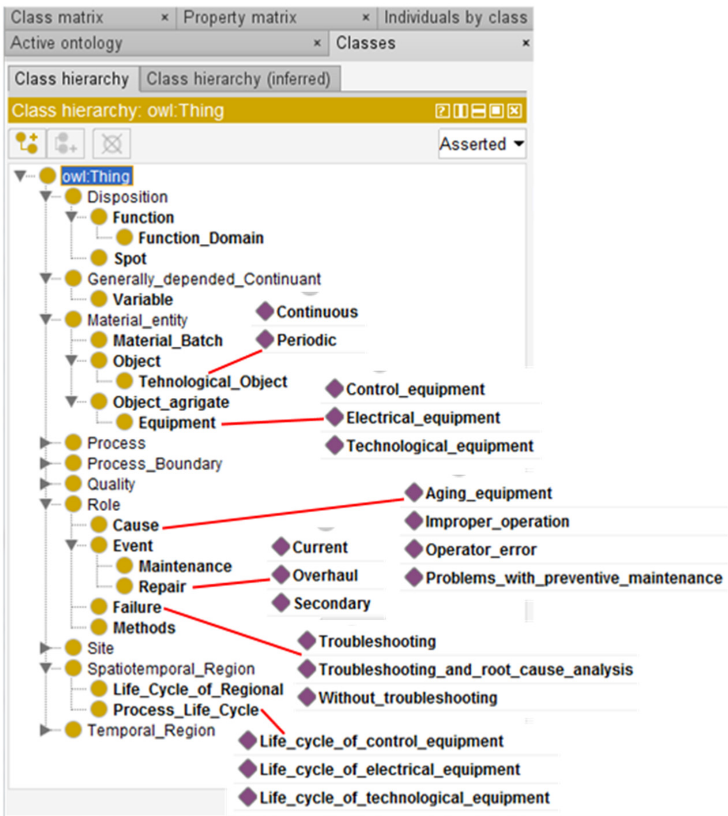

Figure 3. Core ontology class hierarchy and their instances in Protege.

There are relations between the core ontology classes, as shown in Table 1.

Table 1. Object Relations.

Relation	Description
hasCause	It relates breakdowns to their causes.
hasEquipment	It is used for objects that may contain other objects. For example, a technological object may contain technological devices, automation equipment and electrical devices.
hasLifeCycle	Each individual has a life cycle.
hasRepair	It relates breakdowns to repairs.
hasSpot	It relates breakdowns to the device, the device to its location on the process layout. This will allow a universal way to save search time in the ontology.
hasState	It is used for objects that can be in different states. For example, the equipment can be in the following states: working, not working, in need of repair
hasTimeStamp	It relates the time value to some data of measurements and events and include some unit of time.

Figure 4 shows the core ontology structure. The dark blue nodes are classes related to BFO and loaded from outside. The blue nodes are core level classes. They are subclasses for instances of the top ontology. Figure 4 also shows the relations established between ontology classes.

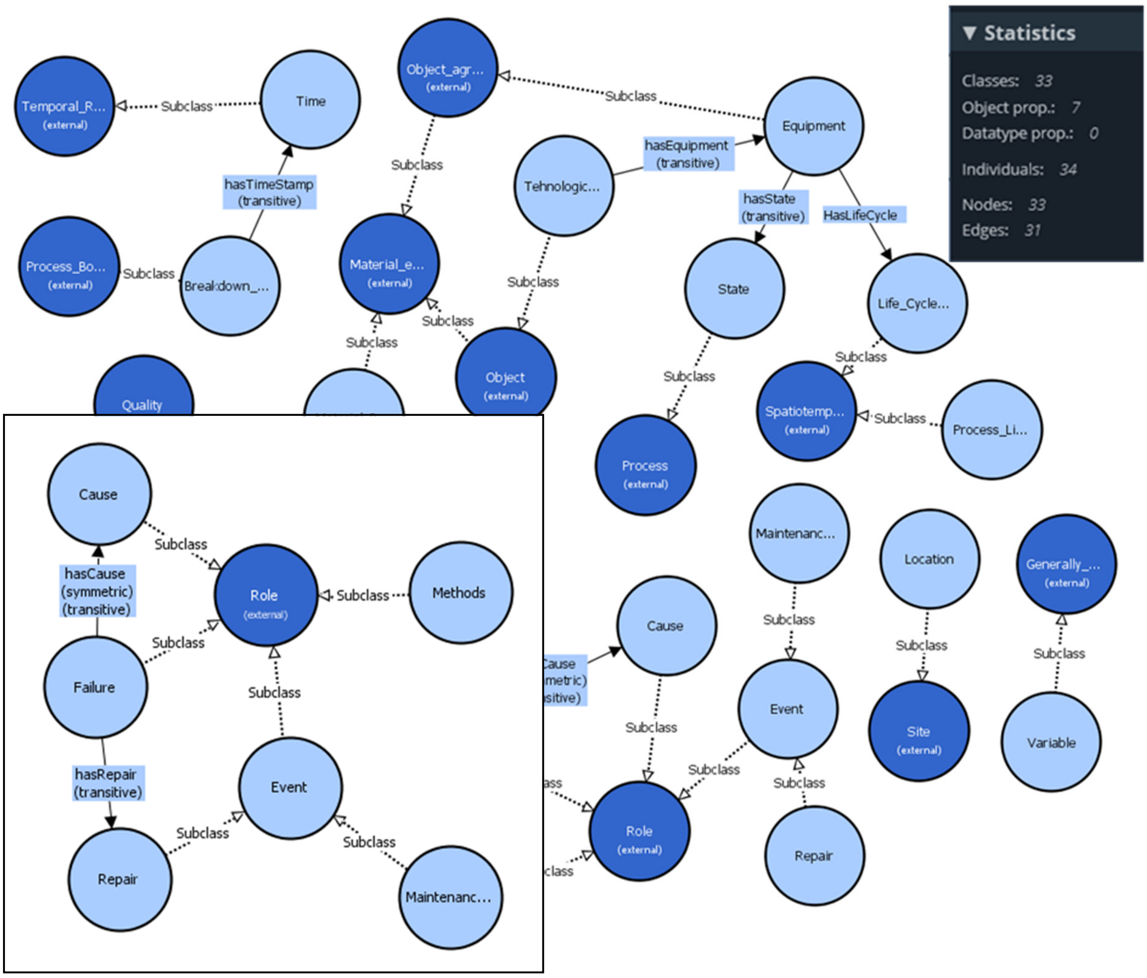

Figure 4. VOWL-graph core ontology.

The core ontology given is a formal ontology for the production environment of diagnosing and predicting the state of a piece of equipment. This approach extends other aspects of the production domain and is the basis for the construction of domain ontologies and guarantees the following: integration with the well-known top-level ontology of BFO; availability of classified theoretical knowledge in the production domain and their semantic compatibility.

Classical approaches to the verification of ontologies include the evaluation of the following criteria [31]: consistency, classification, completeness, conciseness and sensitivity. Verification of the above criteria showed the reasonableness of the constructed ontology. Evaluation of the ontology metric [32–34], which is shown Figure 4 in the upper right corner, is also important. The developed metric is compatible with industrial ontologies presented in open access [35] and can be integrated with them.

This metric corresponds to the core level concept, that is, a minimal but complete set of things. This is important because it provides the core logic for describing the enterprise and is a structured representation of knowledge and judgment. In addition, the core ontology will be used in domain ontologies, so it should contain a minimal set of terms to reduce the resonator time. It will also avoid possible intrackabilities that may arise due to the large number of things at the domain and application levels.

The validity of core ontology was tested using the OWL URL validator: mowl-power.cs.man.ac.uk:8080/validator/, accessed on 4 October 2022. It showed no logical inconsistencies ensuring its compatibility and reusability.

4. Experiment and Results

Any ontology aims at discovering new knowledge on the basis of the relations and axioms embedded in it. A set of typical queries at the core level has been developed (Figure 1). Below are several queries illustrating the formation of new theoretical knowledge. For example, Query 1 shows what types of equipment can be installed on different types of process facilities and what types of lifecycle are inherent in that equipment. Query 2 refers to the BFO and indicates that the Role class (Figure 2) is interpreted at the core level by the following classes: Failure, Cause, Methods and Event (Figure 3). For each of the above classes, instances are shown, except for the Event class, because it has subclasses. Query 3 shows how the complexity of the failure is related to the cause and the type of repair needed.

Any ontology aims at discovering new knowledge on the basis of the relations and axioms embedded in it. A set of typical queries at the core level has been developed (Figure 1). Below are several queries illustrating the formation of new theoretical knowledge. For example, Query 1 (Figure 5) shows what types of equipment can be installed on different types of process facilities and what types of lifecycle are inherent in that equipment. Query 2 (Figure 6) refers to the BFO and indicates that the Role class (Figure 2) is interpreted at the core level by the following classes: Failure, Cause, Methods and Event (Figure 3). For each of the above classes, instances are shown, except for the Event class, because it has subclasses. Query 3 (Figure 7) shows how the complexity of the failure is related to the cause and the type of repair needed.

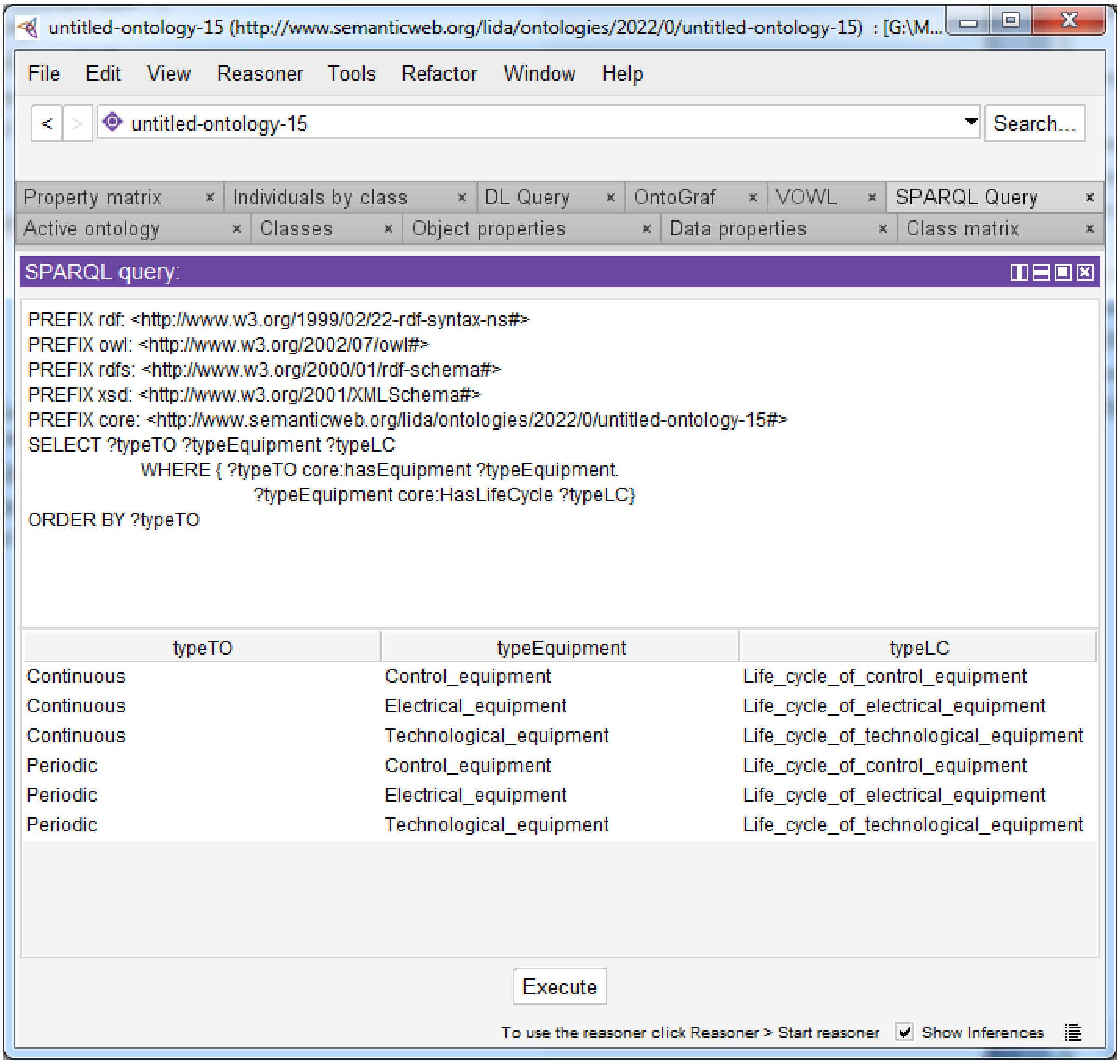

Figure 5. Query 1.

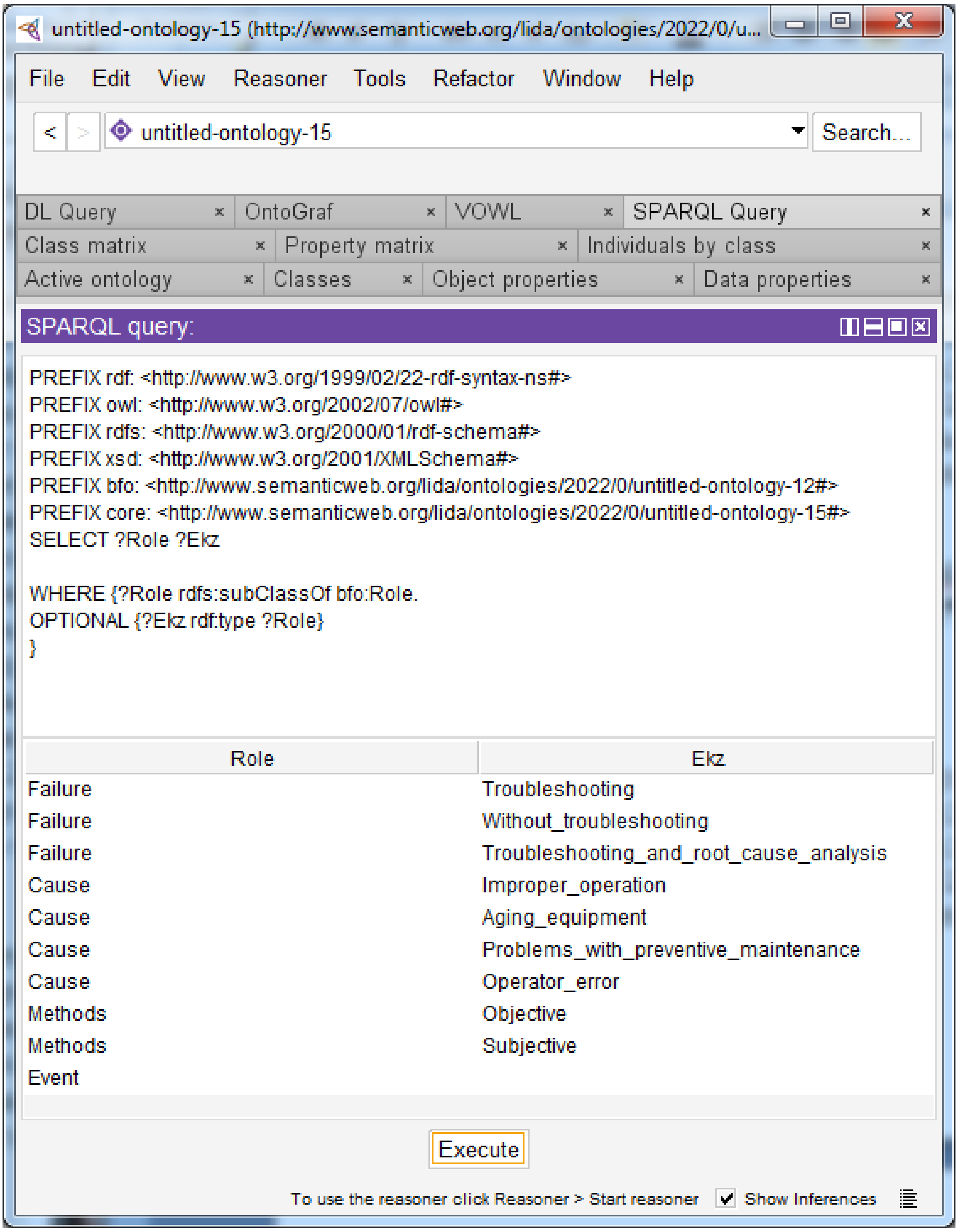

Figure 6. Query 2.

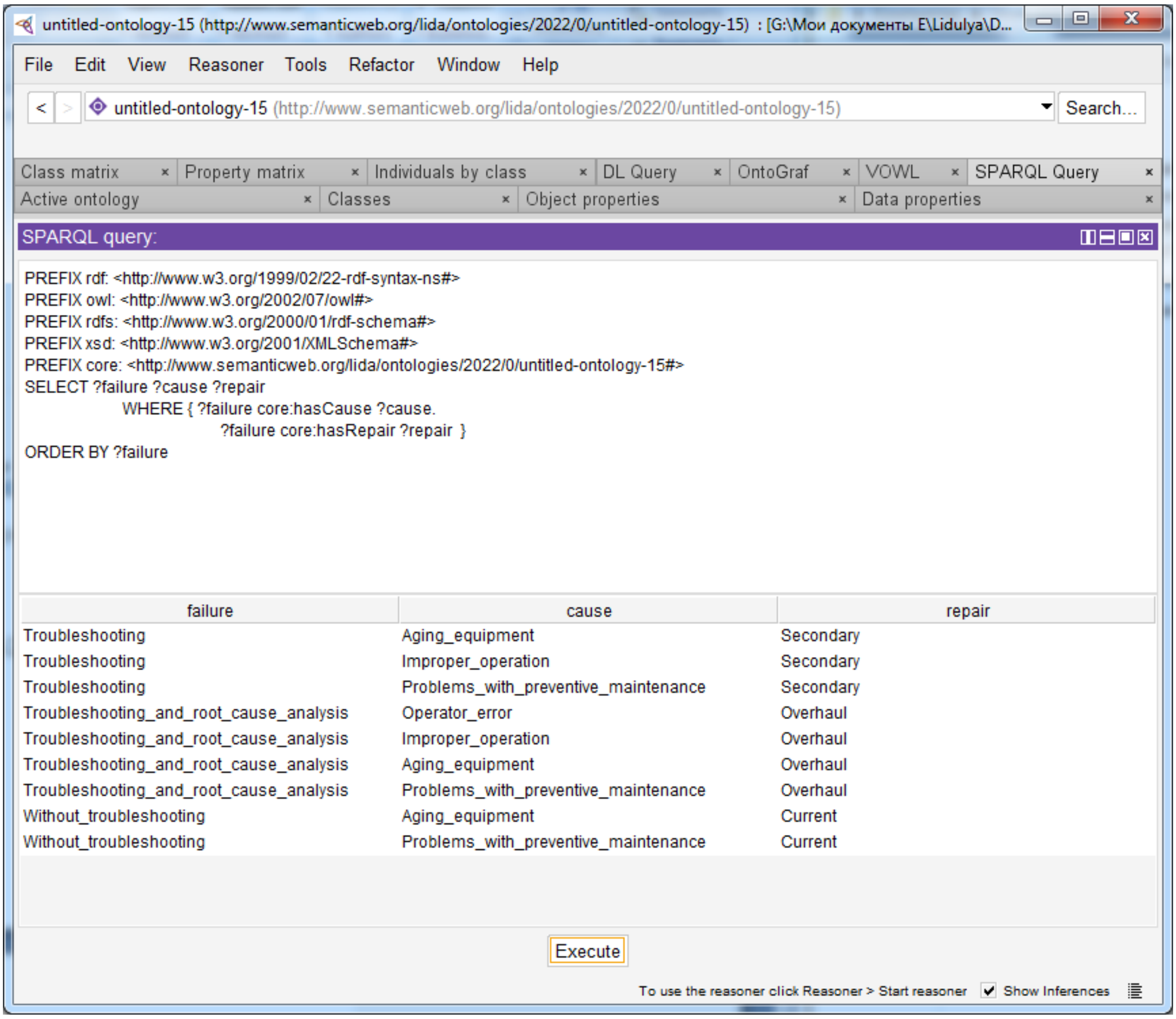

Figure 7. Query 3.

5. Conclusions

This paper presents the result of the core ontology of the conceptual model of the state of equipment (control equipment, electrotechnical equipment), which systematizes theoretical knowledge and basic concepts of industrial enterprise and was developed in accordance with the fundamental concept of BFO. A set of classes defining the cause, type of failure, equipment and location where it occurred was developed. The structure takes into account the equipment hierarchy according to the ISA 95 standard. It contains 33 classes, 7 object properties and 34 individuals. Based on the evaluation of the built ontology, it is proven that it is conceptually transparent and semantically clear, so it is suitable for theoretical knowledge transfer, sharing and retrieval.

This ontology is domain-independent and abstracts assets that exist in all domains. The theoretical knowledge-oriented research uses the abstraction and decomposition of knowledge about the technical and technological components of the industrial enterprise, which provides: a single consistent definition of terms, a simple understanding of the relations between assets, integration with the organizational component of the enterprise, knowledge sharing and reusability. It is implemented in OWL language and is compatible with other ontologies and can be reused.

The use of the developed ontology will ensure increased efficiency due to its functions as:

- a single database of knowledge preservation, which stores information throughout the entire life cycle of the device;
- a single knowledge base for modeling the subject area, which works on the usual historical database and establishes the necessary knowledge;
- a means of information support for management decision-making, which works with open ontological databases in the network and serves to present auxiliary information.

In the future, it is planned to develop a domain ontology, which will specify and systematize typical production equipment, methods and means of monitoring, diagnosing and forecasting equipment conditions.

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