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Ontology-Based Monitoring of Production Processes Using Industrial Sensor Data

Karol Chrzanowski, Dariusz Dobrowolski

Kielce University of Technology, Faculty of Management and Computer Modelling, Poland

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Abstract
The rapid development of solutions based on modern information technologies (i.e., Semantic ML or ChatGPT) has emerged in the industry and its management methods. During the analysis of the possibilities of using these technologies in the processes of operation and maintenance of machines and devices, the options of using ontology for monitoring production processes based on measurement data obtained from vibration sensors located on the CP Factory production line in the Laboratory of Modeling of Intelligent Production Systems of the Kielce University of Technology were considered. The article aims to present the possibility of using measurement data to build an ontology of machine and equipment maintenance processes and to indicate the possibility of using it to create scenarios of events affecting the monitoring of appropriate operational parameters of the production process with the use of controlled natural language.

Keywords
ontology, intelligent decision support systems in manufacturing, production monitoring, Industry 4.0, data measuring, intelligent system techniques and applications.

Introduction

The purpose of this article is to present the possibility of using measurement data to build an ontology and to indicate its applicability in creating event scenarios for monitoring operating parameters in a production process using controlled natural language. By enabling human-machine communication through an accessible language, this work aims to reduce both the overexploitation and excessive damage to the equipment by improving production process monitoring. One of the answers to the problem of organizing data efficiently is the use of semantic technologies by describing knowledge bases with ontology-based systematization systems. This is a forward-looking method of describing the large datasets and the relationships between them that are generated by modern industry. However, in modern times, when ontologies are used to describe knowledge bases (data and the detailed network of relationships and dependencies between them) in information systems, among others, the definition of Tom Robert Gruber is used (Gruber, 1993), which describes ontologies as "the formal, explicit specification of a shared conceptualization."

A significant feature of ontology-based systems is the preservation of ontological commonality. If an environment from a given domain is accepted within ontological structures, the resulting information systems, even if created by unrelated teams, will be interoperable (Goczyła, 2011). The creation of ontologies is based on five main principles identified by Gruber:

- Clarity – the created ontology should effectively convey the intended meaning of the terms it describes, and the definitions themselves should under no circumstances be laced with a lack of objectivity. The description of an element must be complete, expressed using natural language, and should make use of formal axioms (Grzelak, 2013).
- Consistency – the ontology should use the mechanism of inference (new assertions are created based on concepts already known to the user of the ontology, which are accepted as accurate), and the axioms themselves must be logical and consistent, also in the case of concepts defined in an informal form. The ontology loses consistency if the sentence derived from the axioms contradicts the definition or example given (Gliński, 2005).

***Corresponding author**: Dariusz Dobrowolski – Faculty of Management and Computer Modelling, Kielce University of Technology, e-mail: d.dobrowolski@tu.kielce.pl*

- Extensibility – already at the stage of designing the ontology, you need to keep in mind the future of the created system, it should use a standard dictionary with preservation of the basis of definitions from the entire scope, with the possibility of making (and deleting) in the future new elements based on the existing dictionary, without having to change it.
- Minimal formalization commitment – conceptualization should be guided at the level of knowledge without reliance on specific symbols.
- Minimal ontological commitment – an ontology should require as little ontological commitment as possible to support knowledge sharing, it should contain as few assumptions and worldview-shaping assertions as possible – it must be unbiased (Gruber, 1993).

Using an ontology and its graphical representation makes it even easier to find specific elements in an already well-ordered structure, but also makes it more efficient to share its resources with others. Ontologies, defined as formalized knowledge models for natural language engineering, knowledge engineering, and information systems engineering (Bajerowska, 2017), are characterized by transparency; a new user can rapidly understand the organizing principle in the knowledge set in use. A properly created and managed structured data set can be continuously developed, even by wide groups of experts in a particular field, implemented in various applications, such as web technologies, created to share resources (e.g. encyclopedic), or to store data for internal company needs, for further processing (e.g. to use visualization techniques in graphical form, which usually translates into higher efficiency in navigating and assimilating resources). The use of knowledge bases is possible in the industry. The information contained in them can be in an expansive range, for example, the mesh of relationships between the materials used to produce a product, which links to suppliers, employees, means of transport, machines, production lines, and even sensors to identify abnormalities and other elements needed in the production process, which should be stored and organized in a knowledge base.

Applying the concepts of ontology construction and operation, combined with an object-oriented view of information systems, accelerates the adoption of industry and scientific standards. The principles presented define a clear path for creating knowledge based on semantic technologies. This allows the developed software to be fully optimized and prepared for commercial applications requiring high performance. These principles are used in describing ontologies using Controlled Natural Language (CNL), which is easy for humans to understand, to convert them into RDF or OWL, languages used by devices on the Semantic Web.

From Fig. 1, an example of an ontology written in natural language concerning the Kielce University of Technology is presented. Fluent Editor software from Cognitum S.A. was used for this purpose.

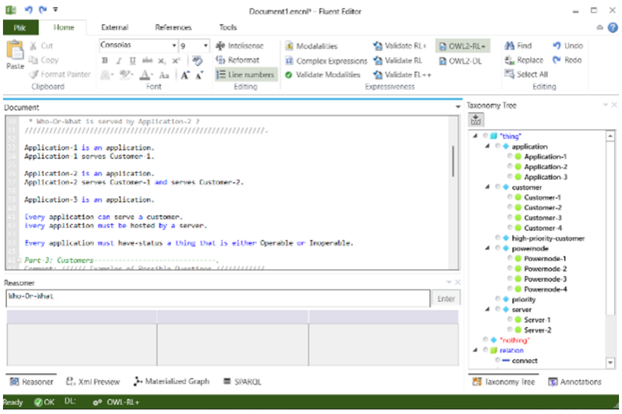

Fig. 1. An example of an ontology written in natural language. Source: own work

Industry 4.0

Manufacturing companies that are serious about their future and the best path forward strive to achieve excellence in their processes. With this approach, they set successive goals to which, step by step, they move at their own pace depending on the circumstances and competitive environment in which they find themselves.

Proper design and organization of production processes to ensure efficient production flow is a critical aspect of achieving the set goals (Szatkowski, 2014). Over the past few centuries, humanity has made significant progress in the context of the development of civilization (especially since the invention of the steam engine and the improved way of working with wrought iron in 1784 by Henry Cort), and especially within manufacturing, transportation, and industry in general.

Humanity is currently in the stage of the fourth industrial revolution, characterized by the attributes of the Web and the Internet, with a fifth revolution increasingly looming on the horizon, looking at aspects of human interoperability with production-assist robots. Fig. 2 provides a breakdown of the four major industrial revolutions and the components that characterize each.

Industry 4.0 builds on the inventions and concepts of the digital revolution (Industry 3.0) by introducing improvements and increased levels of automation in production processes. Industry 4.0 significantly supports production supervisors directly and indirectly,

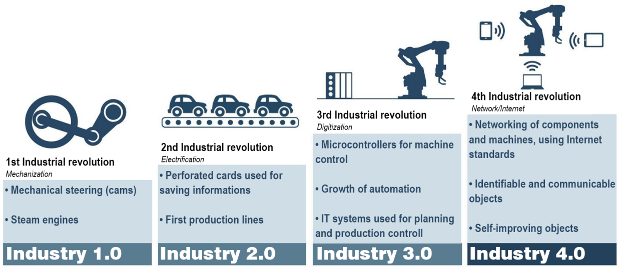

Fig. 2. Four major industrial revolutions.
Source: Siuta-Tokarska, 2021

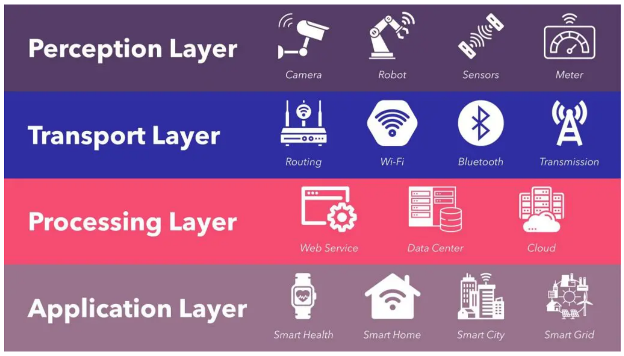

Fig. 3. Layers of IoT architecture.
Source: Simmons, 2024

thanks to the ability to monitor and control the production process in real-time, e.g., through web technologies. Machines, in this concept, are connected into networks, easily managed from a central point, which is another step to significantly increase the efficiency of production in factories, as well as improving the ease of human-machine communication (Moczydłowska, 2022). Manufacturers, on the other hand, can get help in responding to individual customer requirements.

Internet of Things

The term for a network of physical objects – devices, measuring elements, machines, equipped with sensors, software, and other technologies designed to communicate and exchange data with other devices using the Web is referred to as the Internet of Things – IoT (Gohale et al., 2018). Over the past few years, IoT has become one of the most essential technological concepts in the 21st century. Considering that everyday objects ranging from kitchen appliances to cars can connect and use innovative functions, it is unsurprising that similar concepts of human-machine communication are being applied to industry. The use of cloud computing, big data, and analytics enables physical objects to collect and share data with minimal human resources and negligible human intervention. Connections between the various devices ensure the creation of a grid of information in the production process, making it possible to communicate with each other, detect errors, determine the production speed, or anticipate possible irregularities (Fig. 3) (Oracle, 2024).

Ontology in Industry 4.0

To facilitate the implementation of Industry 4.0, it is necessary to provide a suitable medium for humans to cooperate with machines. The ability to communicate effectively between parties is a significant aspect of the management of company resources, because it enables the correct use of equipment resources, for example, on the production line within the manufacturing unit.

The key element is to make decisions based on the possible benefits of leveraging Industry 4.0 capabilities and to orient the company to follow the path of a modern manufacturing plant. Decisions and steps based on it must be made at every level of the organization, relying on restructuring plans if necessary.

Ontologies are versatile tools for capturing and sharing common knowledge in many areas of everyday life. In the context of industry issues, this statement applies to manufacturing enterprises in line with modern industrial concepts, among others. Ontology-based technology is being used in manufacturing, for example, as Context-as-a-Service (CaaS) platforms that focus, for instance, on decision support, not based on pure data stored in a knowledge base or a classic database of data, but on data describing the data, relationships, and connections between them, which allows information systems to make conclusions based on a more modest body of information, but laced with "experience" (Sampath Kumar, et al., 2019).

This way of working, combined with the focus on technologies using ontologies on transparency and the elimination of ambiguities in the data, allows machines to follow a cause-and-effect sequence and facilitate knowledge sharing within the concept of the Semantic Internet, or for internal use, usable in the manufacturing enterprise (Olszewska & Allison, 2018).

Creation of Ontological Models

Modeling with ontology models can be used for Business Process Re-engineering (BPR) or for developing and adopting control systems on a larger scale. Ontologies about Industry 4.0 play a significant role in the processes of system modeling and the creation of "digital twins," i.e., virtual computer objects representing human activities, supporting the testing of prototypes, or supporting the analysis of possible design errors and making necessary corrections.

An example of the practical application of modeling is the development of RAMI 4.0, an industrial reference modeling system in line with Industry 4.0. It refers to the dissemination and improvement of the capabilities of Human Machine Interface (HMI) systems used to control machines by humans (Nagy et al., 2021).

The process of creating an ontology (Fig. 4) in industrial applications is divided into three basic tasks that experts follow when creating advanced ontology systems used in manufacturing enterprises (Nagy et al., 2021):

1. Data collection
   (a) Finding relevant factors in the quantitative and qualitative form of the production process, and then collecting data from the sources available in the scope environment,
   (b) Performing the process of mining and preparing the raw data for analysis, and then further processing the resulting set into a set based on ontological concepts.
2. Ontological modeling
   (a) Establishing the basic structure of the production process network and including the relationships and dependencies occurring between groups and classes in the ontology to be created.
   (b) Determination of descriptive and influential factors of the system as weight parameters, requirements, or elements having the possibility to improve their values in the process of optimizing elements.
   (c) Creating the desired ontology using appropriate software (including ontology editors and graph knowledge bases).
3. Advanced manufacturing analytics
   (a) Analyzing previously defined descriptive and influential factors using database querying and statistical analysis.
   (b) Generating multi-layered networks based on ontologies and graph knowledge bases.

The measurements were made as part of a collaboration between WSA Solutions, Cognitum S.A., and Kielce University of Technology in the implementation of the WeSenseAll project (April 2022). Due to the characteristics of production line equipment, their databases can store data for a limited period, so the goal of the project was to analyse better solutions for collecting and storing data for later use, such as for predicting future operations (in the project, the collected data was used to build a predictive model).

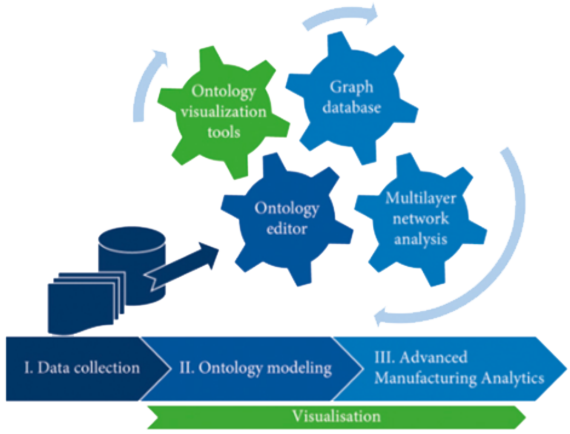

Fig. 4. The main stages of creating ontological models. Source: Nagy et al., 2021

Three options were submitted for consideration during selection:

1. Building a dedicated service for collecting data from instances (creating a server, sending queries to each example for a new set of data).
2. Launching a centralized database for storing data over long periods (Implementation of a database solution that concentrates data in a central repository).
3. Use of cloud solutions dedicated to storing and querying data (Use of the infrastructure of the selected cloud provider (in this case, Microsoft Azure) to store data).

After analysing the aspects above, it was decided to adopt a cloud solution, allowing you to determine how often data is retrieved from an instance, having high configuration and expansion capabilities (due to the nature of scalability of cloud service solutions). It facilitated remote access, secured by authentication methods to Microsoft Azure.

Measurement Data Collection

The sensors were placed on two modules located on the laboratory's production line (Fig. 5):

1. Module 2 – on the column of a six-axis robotic arm (CP-F-RASS).
2. Module 4 – on the housing of an assembly press (CP-AM-PRESS) that closes the lids of boxes produced in the lab's process.

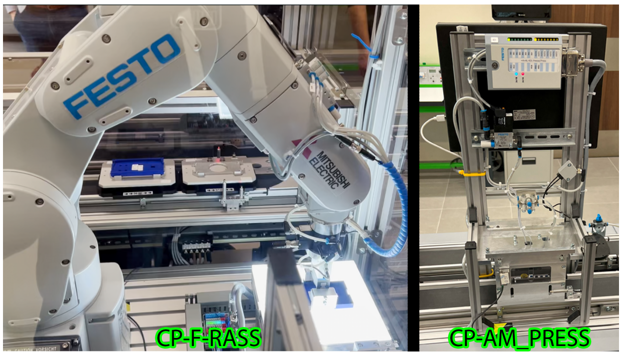

Fig. 5. Devices that were equipped with sensors during the study. Source: own work

Measurements taken as part of the WeSenseAll project during the operation of the CP-F-RASS robot, at the Modeling Laboratory for Intelligent Manufacturing Systems at Kielce University of Technology, include about 13950 readings each, over two time ranges (denoted in the file as two different reading identifiers).

A slice of the contents of the source.csv file is shown in Fig. 6. The robot, while the measurements were in progress, performed its assigned tasks through the MES system – assembling PCBs and cylindrical fuses in the appropriate places prepared for them.

1	id	x_mean_	y_mean_	z_mean_	value_me	timestam	x_max_1s	y_max_1s	z_max_1s	value_ma	x_min_1s	y_min_1s	z_min_1s	value_mi	x_median	y_median
2	349568	0.142695000	0.08995	0.12854	23.214125	##########	0.15997	0.0941	0.13069	26.61650000	0.12542	0.0858	0.12639	22.052	0.142695000	0.08995
3	349569	0.142695000	0.08995	0.12854	23.214125	##########	0.15997	0.0941	0.13069	26.61650000	0.12542	0.0858	0.12639	22.052	0.142695000	0.08995
4	349570	0.142695000	0.08995	0.12854	23.214125	##########	0.15997	0.0941	0.13069	26.61650000	0.12542	0.0858	0.12639	22.052	0.142695000	0.08995
5	349571	0.142695000	0.08995	0.12854	23.214125	##########	0.15997	0.0941	0.13069	26.61650000	0.12542	0.0858	0.12639	22.052	0.142695000	0.08995
6	349572	0.11284	0.10827	0.16411	22.1111	##########	0.11284	0.10827	0.16411	22.1308	0.11284	0.10827	0.16411	22.0914	0.11284	0.10827
7	349573	0.11284	0.10827	0.16411	22.1111	##########	0.11284	0.10827	0.16411	22.1308	0.11284	0.10827	0.16411	22.0914	0.11284	0.10827
8	349574	0.10604	0.11943	0.1435	22.16035	##########	0.10604	0.11943	0.1435	22.1702	0.10604	0.11943	0.1435	22.1505	0.10604	0.11943
9	349575	0.10604	0.11943	0.1435	22.16035	##########	0.10604	0.11943	0.1435	22.1702	0.10604	0.11943	0.1435	22.1505	0.10604	0.11943
10	349576	0.11795	0.1004	0.13714	22.128425	##########	0.11795	0.1004	0.13714	22.14235	0.11795	0.1004	0.13714	22.1145	0.11795	0.1004
11	349577	0.11795	0.1004	0.13714	22.128425	##########	0.11795	0.1004	0.13714	22.14235	0.11795	0.1004	0.13714	22.1145	0.11795	0.1004
12	349578	0.14038	0.1016	0.147	22.15417500	##########	0.14038	0.1016	0.147	22.1674	0.14038	0.1016	0.147	22.14095	0.14038	0.1016
13	349579	0.14038	0.1016	0.147	22.15417500	##########	0.14038	0.1016	0.147	22.1674	0.14038	0.1016	0.147	22.14095	0.14038	0.1016
14	349580	0.14179	0.08396	0.16343	22.18869999	##########	0.14179	0.08396	0.16343	22.1958	0.14179	0.08396	0.16343	22.1816	0.14179	0.08396
15	349581	0.14179	0.08396	0.16343	22.18869999	##########	0.14179	0.08396	0.16343	22.1958	0.14179	0.08396	0.16343	22.1816	0.14179	0.08396
16	349582	0.10793	0.1118	0.13688	22.19062499	##########	0.10793	0.1118	0.13688	22.19234999	0.10793	0.1118	0.13688	22.1889	0.10793	0.1118
17	349583	0.10793	0.1118	0.13688	22.19062499	##########	0.10793	0.1118	0.13688	22.19234999	0.10793	0.1118	0.13688	22.1889	0.10793	0.1118
18	349584	0.12695	0.11533	0.19587	22.240575	##########	0.12695	0.11533	0.19587	22.2578	0.12695	0.11533	0.19587	22.22335	0.12695	0.11533
19	349585	0.12695	0.11533	0.19587	22.240575	##########	0.12695	0.11533	0.19587	22.2578	0.12695	0.11533	0.19587	22.22335	0.12695	0.11533
20	349586	0.12016	0.13855	0.16141	22.252925	##########	0.12016	0.13855	0.16141	22.25455000	0.12016	0.13855	0.16141	22.2513	0.12016	0.13855
21	349587	0.12016	0.13855	0.16141	22.252925	##########	0.12016	0.13855	0.16141	22.25455000	0.12016	0.13855	0.16141	22.2513	0.12016	0.13855
22	349588	0.11987	0.09219	0.10473	22.283625	##########	0.11987	0.09219	0.10473	22.2944	0.11987	0.09219	0.10473	22.27285	0.11987	0.09219
23	349589	0.11987	0.09219	0.10473	22.283625	##########	0.11987	0.09219	0.10473	22.2944	0.11987	0.09219	0.10473	22.27285	0.11987	0.09219
24	349590	0.132275	0.094275	0.155535	22.2772875	##########	0.13777	0.10605	0.1796	22.28895	0.12678	0.0825	0.13147	22.2633	0.132275	0.094275
25	349591	0.132275	0.094275	0.155535	22.2772875	##########	0.13777	0.10605	0.1796	22.28895	0.12678	0.0825	0.13147	22.2633	0.132275	0.094275
26	349592	0.132275	0.094275	0.155535	22.2772875	##########	0.13777	0.10605	0.1796	22.28895	0.12678	0.0825	0.13147	22.2633	0.132275	0.094275
27	349593	0.132275	0.094275	0.155535	22.2772875	##########	0.13777	0.10605	0.1796	22.28895	0.12678	0.0825	0.13147	22.2633	0.132275	0.094275
28	349594	0.09906	0.13566	0.12867	22.28235	##########	0.09906	0.13566	0.12867	22.2887	0.09906	0.13566	0.12867	22.276	0.09906	0.13566
29	349595	0.09906	0.13566	0.12867	22.28235	##########	0.09906	0.13566	0.12867	22.2887	0.09906	0.13566	0.12867	22.276	0.09906	0.13566
30	349596	0.14074	0.10651	0.14849	22.33662499	##########	0.14074	0.10651	0.14849	22.3526	0.14074	0.10651	0.14849	22.32065	0.14074	0.10651

Fig. 6. File used in the WeSenseAll project containing sensor readings, among other things. Source: own work

A file was created based on the source.csv file, which was used to build a measurement data ontology. The structure of the file (hereafter referred to as data_ontology.csv) is shown in Fig. 7. It includes information on:

1. Measurement ID.
2. Timestamp (YYYY-mm-dd hh:mm:ss) – in the ontology under development, the first measurement period starts at 10:00:00, while the second one starts at 15:00:00, with a clear break between the data, which helps in further sample visualization.
3. X, Y, and Z components of acceleration.
4. The average of the acceleration components.
5. Temperature.

A	B	C	D	E	F	G
ID	timestamp	X	Y	Z	Mean	Temp
1	2023-09-09 10:00:00	0,142695	0,08995	0,12854	0,120395	23,21413
2	2023-09-09 10:00:01	0,142695	0,08995	0,12854	0,120395	23,21413
3	2023-09-09 10:00:02	0,142695	0,08995	0,12854	0,120395	23,21413
4	2023-09-09 10:00:03	0,142695	0,08995	0,12854	0,120395	23,21413
5	2023-09-09 10:00:04	0,11284	0,10827	0,16411	0,128407	22,1111
6	2023-09-09 10:00:05	0,11284	0,10827	0,16411	0,128407	22,1111
7	2023-09-09 10:00:06	0,10604	0,11943	0,1435	0,12299	22,16035
8	2023-09-09 10:00:07	0,10604	0,11943	0,1435	0,12299	22,16035
9	2023-09-09 10:00:08	0,11795	0,1004	0,13714	0,118497	22,12843
10	2023-09-09 10:00:09	0,11795	0,1004	0,13714	0,118497	22,12843
11	2023-09-09 10:00:10	0,14038	0,1016	0,147	0,12966	22,15418
12	2023-09-09 10:00:11	0,14038	0,1016	0,147	0,12966	22,15418
13	2023-09-09 10:00:12	0,14179	0,08396	0,16343	0,129727	22,1887
14	2023-09-09 10:00:13	0,14179	0,08396	0,16343	0,129727	22,1887
15	2023-09-09 10:00:14	0,10793	0,1118	0,13688	0,11887	22,19063
16	2023-09-09 10:00:15	0,10793	0,1118	0,13688	0,11887	22,19063
17	2023-09-09 10:00:16	0,12695	0,11533	0,19587	0,14605	22,24058
18	2023-09-09 10:00:17	0,12695	0,11533	0,19587	0,14605	22,24058
19	2023-09-09 10:00:18	0,12016	0,13855	0,16141	0,14004	22,25293
20	2023-09-09 10:00:19	0,12016	0,13855	0,16141	0,14004	22,25293
21	2023-09-09 10:00:20	0,11987	0,09219	0,10473	0,105597	22,28363
22	2023-09-09 10:00:21	0,11987	0,09219	0,10473	0,105597	22,28363
23	2023-09-09 10:00:22	0,132275	0,094275	0,155535	0,127362	22,27729
24	2023-09-09 10:00:23	0,132275	0,094275	0,155535	0,127362	22,27729

Fig. 7. Data file for ontology construction. Source: own work

Building a Lab Ontology

The steps to be taken in the process of building any ontology are:

1. Determining the purpose and scope of the information contained in the system to be built.
2. Collecting the necessary information from the available sources and preparing it into a form that allows storage in the knowledge base.
3. Implementation of the ontology, using the selected information system, and graphical representation of the available resources, e.g. in the form of a graphical knowledge base.

The first step in creating measurement ontologies is building a base structure of a relationship grid to describe the Laboratory for Modeling Intelligent Manufacturing Systems. For this purpose, Fluent Editor software and controlled natural language (CNL) were used to describe the laboratory environment based on CP Factory's production line documentation and internal materials found in the laboratory. CNL is based on the use of simple sentences in English.

By creating a base ontology for the production line of the Intelligent Manufacturing Systems Modeling Laboratory, a "skeleton" has been made to which measurement data can be attached. To do this, you need to specify the assignment of sensors to specific machines, as shown in Fig. 8.

```
Robot-Temperature-Sensor is a sensor.
Robot-Vibration-Sensor is a sensor.
Press-Vibration-Sensors is a sensor.

The-"CP-F-RASS" has-equipment Robot-Vibration-Sensor.
The-"CP-F-RASS" has-equipment Robot-Temperature-Sensor.
The-"CP-AM-PRESS" has-equipmen Press-Vibration-Sensor.
```

Fig. 8. Building a measurement data ontology – defining sensors. Source: own work

The next step is to start supplementing the ontology with measurement data. Based on the contents of the previously developed data_ontology.csv file, a natural language measurement data structure was developed, consisting of Fig. 9:

1. Assignment of measurement type (Xpart, Ypart, Zpart, Xyz Mean, Temp) to the class "robot measurement".
   - Xpart – X component of the acceleration sensor measurement.
   - Ypart – the Y component of the acceleration sensor measurement.
   - Zpart – Z component of the acceleration sensor measurement.
   - Xyz Mean – the average of the acceleration sensor components.
   - Temp – temperature sensor reading.
2. Assignment of the "measurement date" attribute and timestamp.
3. Assignment of the attribute "measurement value" and the value from the sensor.
4. Information that a particular measurement "is a measurement belonging to" the robot's vibration sensor.

```
Robot-Measurement-Xpart-1 is a robot-measurement.
Robot-Measurement-Xpart-1 has-measurementdate equal-to '2023-09-09 10:00:00'.
Robot-Measurement-Xpart-1 has-measvalue equal-to 0.142695.
Robot-Measurement-Xpart-1 is-measurement-of Robot-Vibration-Sensor.

Robot-Measurement-Ypart-1 is a robot-measurement.
Robot-Measurement-Ypart-1 has-measurementdate equal-to '2023-09-09 10:00:00'.
Robot-Measurement-Ypart-1 has-measvalue equal-to 0.08995.
Robot-Measurement-Ypart-1 is-measurement-of Robot-Vibration-Sensor.

Robot-Measurement-Zpart-1 is a robot-measurement.
Robot-Measurement-Zpart-1 has-measurementdate equal-to '2023-09-09 10:00:00'.
Robot-Measurement-Zpart-1 has-measvalue equal-to 0.12854.
Robot-Measurement-Zpart-1 is-measurement-of Robot-Vibration-Sensor.

Robot-Measurement-Xyz-Mean-1 is a robot-measurement.
Robot-Measurement-Xyz-Mean-1 has-measurementdate equal-to '2023-09-09 10:00:00'.
Robot-Measurement-Xyz-Mean-1 has-measvalue equal-to 0.120395.
Robot-Measurement-Xyz-Mean-1 is-measurement-of Robot-Vibration-Sensor.

Robot-Measurement-Temp-1 is a robot-measurement.
Robot-Measurement-Temp-1 has-measurementdate equal-to '2023-09-09 10:00:00'.
Robot-Measurement-Temp-1 has-measvalue equal-to 23.214125.
Robot-Measurement-Temp-1 is-measurement-of Robot-Temperature-Sensor.
```

Fig. 9. Building a measurement data ontology – measurement data. Source: own work

Given the lack of a tool to convert measurement data into controlled natural language (or into output files such as RDF, or OWL, which are created in Fluent Editor based on the ontology being created in CNL), a simple Python script was created that converts a .csv file into textual data that can be inserted into the ontology in controlled natural language form based on a general schema developed earlier relating to the structure of measurement data in the lab ontology being created.

The lab ontology description created this way, combined with the ontology of measurement data generated during the manufacturing process using the vibration sensor example, can also be queried in Fluent Editor to obtain information about the measurement results, as shown in Fig. 10.

Materialized Graph

```
Who-Or-What is a measurement?
```

<?> is a measurement.	is-measurement-of	has-measurementdate	has-measvalue
Robot-Measurement-Xpart-1	Robot-Vibration-Sensor	2023-09-09 10:00:00	0.142695
Robot-Measurement-Xyz-Mean-1	Robot-Vibration-Sensor	2023-09-09 10:00:00	0.120395
Robot-Measurement-Temp-1	Robot-Temperature-Sensor	2023-09-09 10:00:00	23.214125
Robot-Measurement-Zpart-1	Robot-Vibration-Sensor	2023-09-09 10:00:00	0.12854
Robot-Measurement-Ypart-1	Robot-Vibration-Sensor	2023-09-09 10:00:00	0.08995
Robot-Measurement-Zpart-2	Robot-Vibration-Sensor	2023-09-09 10:00:01	0.12854
Robot-Measurement-Temp-2	Robot-Temperature-Sensor	2023-09-09 10:00:01	23.214125
Robot-Measurement-Xpart-2	Robot-Vibration-Sensor	2023-09-09 10:00:01	0.142695
Robot-Measurement-Xyz-Mean-2	Robot-Vibration-Sensor	2023-09-09 10:00:01	0.120395
Robot-Measurement-Ypart-2	Robot-Vibration-Sensor	2023-09-09 10:00:01	0.08995
Robot-Measurement-Xpart-3	Robot-Vibration-Sensor	2023-09-09 10:00:02	0.142695
Robot-Measurement-Ypart-3	Robot-Vibration-Sensor	2023-09-09 10:00:02	0.08995
Robot-Measurement-Xyz-Mean-3	Robot-Vibration-Sensor	2023-09-09 10:00:02	0.120395
Robot-Measurement-Temp-3	Robot-Temperature-Sensor	2023-09-09 10:00:02	23.214125
Robot-Measurement-Zpart-3	Robot-Vibration-Sensor	2023-09-09 10:00:02	0.12854
Robot-Measurement-Xpart-4	Robot-Vibration-Sensor	2023-09-09 10:00:03	0.142695
Robot-Measurement-Zpart-4	Robot-Vibration-Sensor	2023-09-09 10:00:03	0.12854
Robot-Measurement-Ypart-4	Robot-Vibration-Sensor	2023-09-09 10:00:03	0.08995
Robot-Measurement-Xyz-Mean-4	Robot-Vibration-Sensor	2023-09-09 10:00:03	0.120395
Robot-Measurement-Temp-4	Robot-Temperature-Sensor	2023-09-09 10:00:03	23.214125
Robot-Measurement-Zpart-5	Robot-Vibration-Sensor	2023-09-09 10:00:04	0.16411
Robot-Measurement-Temp-5	Robot-Temperature-Sensor	2023-09-09 10:00:04	22.1111
Robot-Measurement-Xyz-Mean-5	Robot-Vibration-Sensor	2023-09-09 10:00:04	0.128406667
Robot-Measurement-Ypart-5	Robot-Vibration-Sensor	2023-09-09 10:00:04	0.10827

Fig. 10. Querying the ontology for measurement information. Source: own work

Querying can also be more precise, such as expecting a value greater than a certain selected number, as shown in Fig. 11.

Materialized Graph

```
Who-Or-What has-measvalue greater-than 23?
```

<?> has-measvalue greater-than 23.	is-measurement-of	has-measvalue	has-measurementdate
Robot-Measurement-Temp-2	Robot-Temperature-Sensor	23.214125	2023-09-09 10:00:01
Robot-Measurement-Temp-4	Robot-Temperature-Sensor	23.214125	2023-09-09 10:00:03
Robot-Measurement-Temp-3	Robot-Temperature-Sensor	23.214125	2023-09-09 10:00:02
Robot-Measurement-Temp-1	Robot-Temperature-Sensor	23.214125	2023-09-09 10:00:00

Fig. 11. Querying the ontology for more detailed information. Source: own work

Visualization of Ontologies

The created ontology in this form is not a particularly helpful tool for enterprises. Although it contains information about the connections and dependencies between machines and the structure of the laboratory, it lacks a form of graphical representation. Especially when dealing with measurement data, which are practically always saved in tabular form, easy to present, and further processing, it is necessary to find a way to create an accessible and, above all, functional visualization for end users.

As a medium for knowledge representation, it was decided to use Gruff software from the AllegroGraph software package (Franz Inc., 2024) – a multi-platform system for analysis and interactive data visualization. In Fig. 12, a graphical visualization of the created measurement ontology is shown. The presented ontology tends to a central point, which in this case is the Kielce University of Technology, from which subsequent branches of the ontology diverge, forming an increasingly detailed grid. On the connections between the individual nodes, the described relationships between them are present, showing the relationships between classes and objects within the ontology being developed.

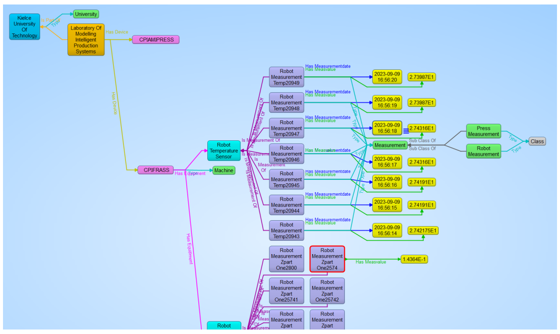

Fig. 12. Created ontology visualized in Gruff (AllegroGraph). Source: own work

In the visualization creation window, the user can customize several display functions to suit requirements, specifying colors, scale, and style of displayed visualizations.

To visualize and analyze basic business data, while providing efficient monitoring of the entire infrastructure and notification functions for unusual events, the Grafana platform was used (Fig. 13) (Grafana, 2024). The panel used plots of real-time waveforms of measurement data stored in the ontology describing the laboratory and the measurement data collected in it. The created visualization can be extended by adding, for example, daily statistics, monthly statistics, and other panels (e.g., calculation of mean, median, and different values).

It is also possible to set critical states (an example red line, shown in Fig. 14, is established in the system as the critical value for that particular displayed graph), and the system alerts the user that the established threshold value has been exceeded. Grafana uses the queried data to check whether the threshold has been exceeded. Suppose it has been exceeded (and

Fig. 13. Sample Grafana dashboard.
Source: Grafana, 2024

an elevated above-normal reading condition persists for a specified time). In that case, it can inform the user that something is happening at the location under investigation, assuming that the data is sent to the visualization in near real-time.

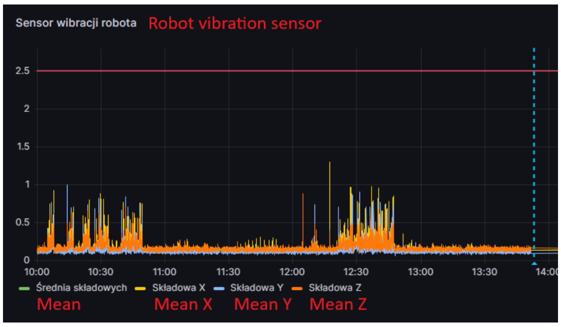

Fig. 14. Determination of a sample critical value.
Source: own work

Summary

The creation of a fundamental ontology describing the Laboratory for Modeling Intelligent Manufacturing Systems of the Kielce University of Technology and its extension to include measurement data showed that it is possible to create an ontology with data that is usually presented in tabular form and use it for visualization purposes and even for monitoring the operation processes of production machines. The use of graphical representation, e.g. in the form of charts, and critical values (e.g. those listed in the specifications and standards of the device) makes it possible to visualize whether the parameters of the production machine are deteriorating over time (e.g. whether there is increased vibration on the production line after a specific time, or based on a vibration sensor whether there is overheating of the device, or checking the tightness of circuits using a pressure sensor used on the production line).

Ontologies and systems based on them are constantly evolving, given the large volumes of data generated today, in all aspects of life and industry, and the need to organize it. In the future, there will be dedicated solutions on the market for collecting measurement data directly into ontological resources.

Based on the research results and the operation of the created system, the hypothesis can be confirmed: ontologies can be used to monitor production processes based on measurement data. Because ontologies are a very flexible tool, the created ontology of the laboratory in combination with measurement data can be extended:

1. Increasing the scope of data, for example, by adding descriptions of production processes to the ontological structures.
2. Describing broader knowledge domains within the unit where the ontology is implemented. For instance, in a scientific unit, one could add relationships between laboratories and supervisors, linking them to their publications and fields of study. This allows for a high degree of data detail and hierarchization.
3. With the development of technology and the introduction of new systems for managing ontologies, in the future, it will be possible to use them in many places to organize knowledge and share information developed in many fields, not only scientific but also social.

The issues raised in the article regarding the application of ontologies and knowledge-based systems in manufacturing, in line with concepts of Industry 4.0 (and likely Industry 5.0 in the near future), are undoubtedly the future in the fields of knowledge storage, representation, and sharing.

The use of modern technologies based on semantics in everyday life (e.g., within the framework of the Semantic Internet) and in industrial applications makes it possible to rearrange and organize collected data sets in a very efficient way, which, concerning production issues, makes it possible to reduce costs and maximize profits, combined with facilitated research processes.

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