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Towards an ontology-based fault detection and diagnosis framework - a semantic approach

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***Abstract*—Fault prediction methods aiming for the real-time monitoring and detection of equipment failures in Industry 4.0 environments, with the integration of internet of things and advanced analytics. The utilization of advanced, data-driven methods such as semantic technologies and ontology-based reasoning can further enhance the efficiency of the development, operation, and integration of fault diagnostic systems and the management of related information. The main contribution is to present an ontology-based fault detection and diagnosis framework to improve the efficiency of fault analysis and detection processes in industrial systems. The framework uses ontologies to represent the complex relationships between different types of data, maintenance events, or equipment failures, and not only relays on failure mode and effects analysis and hazard and operability study but adapts fault tree analysis for semantic reasoning. Additionally, a conceptual domain ontology is proposed, which provides efficient data interoperability in the complex system. An illustrative, wire harness manufacturing-based example presents, that the framework can identify potential failure modes and their causes, and perform anomaly detection and root cause analysis, using the domain ontology with reasoning techniques.**

***Index Terms*—Fault detection, Fault diagnosis, Ontology, Reasoning, FTA, Root cause analysis, FMEA**

I. Introduction

Fault detection and diagnosis are essential in Industry 4.0 systems, as they allow for performing proactive maintenance, reducing downtime, and increasing equipment availability, which leads to cost savings, improved production efficiency and increase competitiveness of the industry [1].

AD (Anomaly Detection) and RCA (Root Cause Analysis) are widely applied techniques to identify and diagnose problems in complex systems, which can cause faults or failures. The anomaly detection method can be applied to a wide range of data sources, including sensor data, log files, and performance metrics, and it can be also used to detect problems in various systems such as manufacturing, transportation and power systems [2]. Anomaly detection uses statistical methods and machine learning algorithms to identify patterns or deviations in the data that indicate a problem or failure [3]. Root cause analysis is a process of identifying the underlying cause of a problem or failure, and it is typically used to identify the underlying cause of a problem or failure after it has been detected [4].

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Begriffseinführung und Literaturverweis -> sehr gut!!

Fault detection methods can support not only the maintenance process and resource optimization, but also can facilitate the industry 5.0 concept, where the human-centered approach is in focus [5]. Industry 5.0 bring novel methods to provide a more resilient and ergonomic environment for workers while ensuring access to solutions, that enable automation and increase the productivity of operators in the production area [6].

To perform standardized investigation, FMEA (Failure Modes and Effects Analysis) and HAZOP (Hazard And Operability Study) are both widely used risk assessment methods in modern industry, however, they both have some limitations. FMEA is primarily focused on identifying potential failure modes and their effects, but it does not allow the evaluation of complex internal relationships of causes [7]. HAZOP is a highly structured and detailed method that can be time-consuming and resource-intensive to conduct, which can make it difficult to apply to large or complex systems [8]. Both methods rely on a manual process and human expertise, which can lead to inconsistencies or errors in results. FMEA and HAZOP are both focused on identifying potential hazards and risks, but they do not provide a comprehensive approach to managing and mitigating those risks, which can make it difficult to implement effective risk management strategies [9].

Analytic tools are needed to perform AD or RCA in a large amount of data, including risk assessment tables, for that goal the FTA (Fault Tree Analysis) can be an adequate way [10]. FTA involves constructing a fault tree, which is a graphical representation of the failure modes and events that lead to the failure [11], and it is also applied in the field of model-driven engineering, which aims to enhance efficiency, quality, and maintainability by utilizing models as the main item in software and system design [12]. In such an application example, FTA has been utilized for safety assessment of robotic systems [13].

To face the problem of fault detection in complex, continuously changing systems, the integration of FMEA and HAZOP with FTA and semantic technologies are considered. This approach makes it possible to provide a more comprehensive approach to fault detection and diagnosis, which can improve the safety and reliability of systems. Ontology-based fault detection and diagnosis method uses semantic technologies,

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such as ontologies and FTA, to enhance traditional fault detection and diagnosis techniques [14]. The application of ontologies can facilitate the representation of the system structure, components, and relationships, as well as possible causes and symptoms of failures, and provide a more comprehensive and accurate representation of the system, leading to more accurate detection and diagnoses of potential failures [15]. Semantic technologies such as RDF (Resource Description Framework) and OWL (Web Ontology Language), are used to represent the information in a machine-readable format, which enables automated reasoning and querying of the represented knowledge [16]. The advantage of using an ontology-based approach is that it allows a more comprehensive and accurate representation of the system, which can lead to more accurate detection and diagnoses of potential failures. Additionally, ontologies can be easily updated as new information becomes available, making this approach highly adaptable to changing conditions.

The goal of this paper is to give an overview of techniques used for fault detection and diagnosis, with a focus on the ontology-based approach. Figure 1 represents the primary problem formulation, which is the detection of faults and related phenomena in a system. An anomaly or symptom is a potential error, while an error is caused by a fault and may cause a failure. Potential faults, errors and failures have descriptive features, such as effect, criticality and severity. The aim during monitoring processes and assets is to perform RCA in order to get fault isolation and diagnosis.

Additionally, this paper aims to introduce an ontology-based framework for fault detection and diagnosis in industrial systems, that integrates semantic reasoning and RCA. This framework utilizes ontologies to depict the intricate connections between different types of sensor data, maintenance events, or equipment failures. The framework not only uses FMEA and HAZOP analysis but also performs FTA for semantic analysis of the production data. By utilizing reasoning and inference techniques, the framework is able to detect potential failure modes and their causes, as well as perform anomaly detection and root cause analysis, using the domain ontology.

This paper is structured as follows: The ontology and graph-aided approaches for model-based analysis are discussed in Section II, where first the ontology-based reasoning of a graph database is presented in Subsection II-A, then different applications of fault detection with semantic technologies are detailed in Subsection II-B. The proposed framework for fault detection and diagnosis is presented in Section III, and an illustrative example of utilization is shown in Section IV. Finally, Section V summarizes the main findings of the research and provides recommendations for future work.

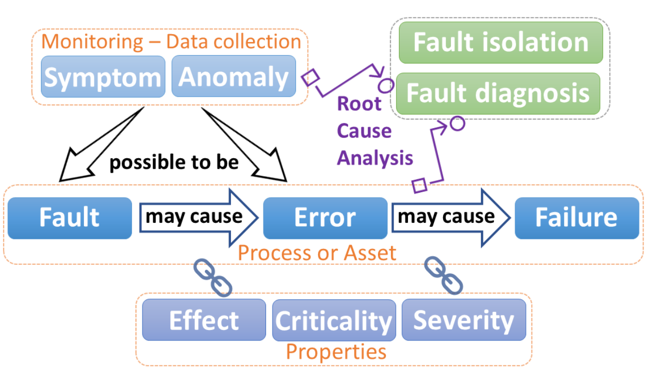

Fig. 1. Fault detection and diagnosis

II. Ontology and graph-aided approaches for model-based analysis

This Section discusses the main aspects of ontology-based network analysis, which aims to detect and diagnose hazards and failures. First, Subsection II-A investigates the utilization of ontology-based reasoning in the context of fault diagnosis, then in Subsection II-B some application scenarios of semantic technologies for fault detection in industrial systems are presented.

A. *Ontology-based reasoning*

Ontology-based reasoning is a method of using formal ontologies, which are structured representations of knowledge, to infer new knowledge from existing knowledge [17]. Application of a reasoning engine or rule-based system is typically involved to analyse relationships between concepts in the ontology, and draw logical conclusions based on those relationships. First, the ontology is used to represent the knowledge in a machine-readable format, then the reasoning engine uses that knowledge to make inferences and generate new knowledge [17].

Ontology-based reasoning can be implemented using a variety of programming languages and formal languages, including: SPARQL (Simple Protocol and RDF Query Language) for querying ontologies and extracting information [18], Prolog for inferring new knowledge from the ontology, Rule-based languages such as SWRL (Semantic Web Rule Language) for expressing rules and constraints in the ontology, or SQWRL (Semantic Query Wrapper and Inference Layer) [19].

An application example utilizes the ontology-based reasoning for supporting work hazard analysis [20], while another one facilitates the safety verification process in model driven engineering [21]. It can be concluded, that the integration of ontology-based reasoning, such as SWRL rules into fault detection and diagnosis frameworks, makes it possible to improve the accuracy and comprehensiveness of failure detection and make the analysis more adaptable to changing conditions.

B. *Fault analysis with semantic technologies*

Fault detection with semantic technologies method involves creating an ontology or knowledge graph, that captures the domain knowledge related to the system, including information about its components, their relationships, and possible failure modes. The ontology is then applied to infer potential faults based on data from the system and other sources, such as sensor readings and historical records. The inferred faults are analysed and prioritized based on their potential impact

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and the likelihood of occurrence. By utilizing the domain-specific knowledge represented in the ontology, this approach may enable a more precise and effective fault detection.

As a utilization example, a semantic cloud architecture framework has been proposed, based on a domain ontology, which addresses challenges such as data collection and analysis for predictive maintenance [22]. While, a study proposed a novel hybrid approach in manufacturing processes, combining data mining and semantics, using chronicle mining to detection failures of industrial machinery. Additionally, the MPMO (Manufacturing Predictive Maintenance Ontology) with its rule-based extension has been developed to predict temporal constraints of failures and represent results formally, resulting in the construction of SWRL rules for predicting the occurrence time of machinery failures in the future [23]. The procedure begins by pre-processing raw industry data sets to create pairs of events and time-stamps, with each sequence ending in a failure event. Next, frequent pattern mining algorithms are applied to the pre-processed data to identify patterns that indicate machinery failures. Finally, mined patterns are used to generate SWRL-based predictive rules through the use of semantic technologies. These rules allow semantic reasoning over individuals in ontologies, and aid in decision making [23].

A further study proposed a method for combining construction process knowledge with ontological modeling and semantic inference to improve the management of risks and safety in the construction process [24]. A meta-ontology model has been proposed that integrates knowledge about risks with objects that monitor them and can be adapted for specific applications to serve as the foundation for a knowledge-based risk management system [24].

so many combinations - ok this is just an overview ...

III. Proposed Framework and Domain Ontology

This Section proposes the ontology-based fault detection and diagnosis framework and presents a structure for a domain ontology.

Figure 2 represents the proposed methodology, which two main segments are the *Semantic annotation* and the *Reasoning*, that can detect or predict anomalies and faults, and investigate the causes of a potential failure, using the created knowledge graph. Sources of these blocks are as follows: Ontology scheme for the contextualized data model, SWRL rules for the semantic-based reasoning, and the *Data extraction* block. Several structured, and unstructured data sources are interlinked, such as the result of FMEA and HAZOP studies for historical data, the industrial standards to ensure re-usability and FTA to detect root causes. FTA is a key element in the framework, as the result of the path- and cut-sets serves as the basis of the ontology-based reasoning. Additionally, the *Production process* segment provides the data about the complex production environment, which has to be pre-processed. The data extraction includes processes, such as parsing, segmentation or aggregation of data. The *Semantic annotation* block creates the *Knowledge graph*, using the taxonomy and the extracted data. During the *Reasoning* part of the methodology fault diagnosis

see Fig. 3 ??

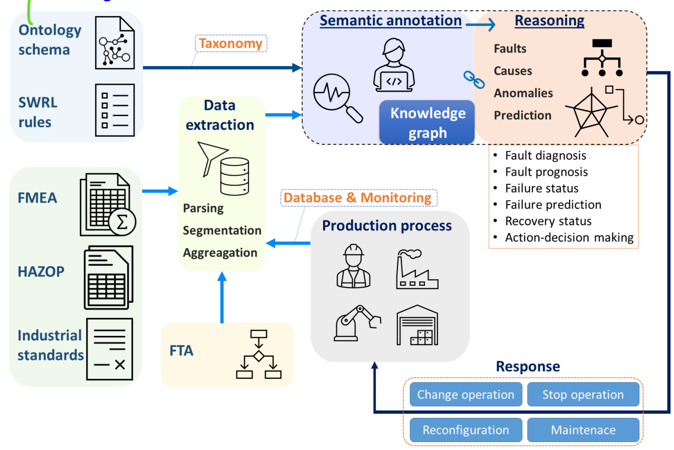

Fig. 2. The proposed methodology for ontology-based fault detection and diagnosis

and prognosis, failure prediction, recovery and failure status check and decision-making are performed. The result of the framework is the *Response*, which is bypassed to the *Production process* segment. A response of the Data enrichment and Reasoning segments can be e.g. the following production orders: Change operation, Stop operation Reconfiguration or Maintenance.

Figure 3 shows the structure of the conceptual ontology. The ontology is based on FMEA analysis, HAZOP study, the MPMO Ontology [23], an ontology-based FMECA modeling approach [25], the FOLIO ontology [26] and the SOSA/SSN ontology [27]. Additionally, several industrial standards have been considered during the ontology modeling, which supports the integration of enterprise and control systems in manufacturing and process environments, performs predictive maintenance, and condition monitoring and diagnostics of machines [28]–[30].

Six different sub-ontologies are defined, such as ISA physical model ontology, Diagnosis ontology, Reasoning ontology, Response ontology, Monitoring ontology and Property Ontol-

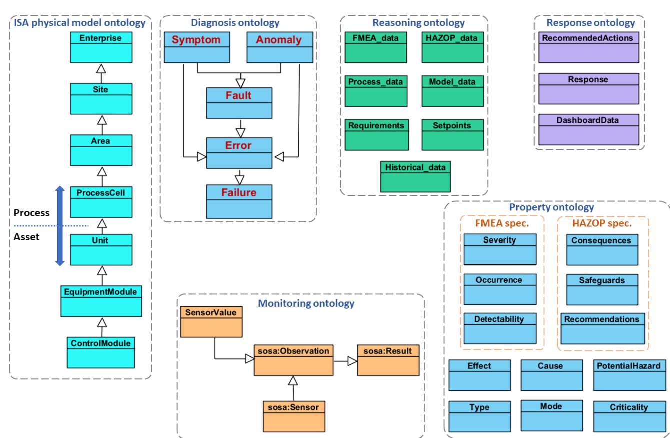

Fig. 3. The structure of the conceptual domain ontology for fault detection and diagnosis

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ogy. All six parts are in relation with each other, however, to provide a more general and transparent figure, this structure does not contain the object properties within ontology classes. The *ISA Physical model ontology* gives the hierarchical structure of the investigated manufacturing system or enterprise, where any element below the Unit level can be an asset, such as a specific workstation, while above this level different types of processes are defined, such as a specific production line. In this way it is possible to analyse either process or device related failures as well. The *Diagnosis ontology* contains the possible symptoms, anomalies, faults, errors and failures, which may occur in the complex system. The *Monitoring ontology* stands for the semantic interpretation of all sensor readings of the process. The *Property ontology* contains all of the descriptive factors about the analysis including but not limited to FMEA specific properties, such as Severity, Occurrence or Detectability, HAZOP specific properties, such as Consequences, Safeguards or Recommendations. Additionally, some general properties are also defined, such as Effect, Cause, PotentialHazad, Type, Mode or Criticality. The *Reasoning ontology* block contains all the already available information as Process and Model data, FMEA and HAZOP data, Requirements, Setpoints and Historical data. Finally, the *Response ontology* stores the following elements of the conceptual domain ontology, such as Recommended actions, Response and Dashboard data.

End of the approach and now: butter by de fische

IV. Illustrative application

This Section aims to present an application scenario of the proposed framework. A previous case study of the authors has been applied, that analysis a wire harness manufacturing process [31].

The investigated process step includes the manual attachment of a terminal to a connector. The example relies on detecting a slowing trend in the production process that alters from the ideal condition, which may have a variety of causes. The time trend change is compared to the standard deviation of the activity times, and if it is higher than the limitation, a fault may occur in one of the process segments. Based on FMEA, it can be stated, which factor has the highest probability of occurrence, therefore that one will be examined first.

Figure 4 represents a fault tree analysis of this increased activity time *symptom*, which has been observed by a time series analysis. The possible *causes* of the effect are grouped, from the concept of ”6Ms of production” into *possible sources* such as material, method, machine, milieu, manpower and measurement [32]. Additionally, the related information sources for *detection* of the nine different causes are denoted in orange frame in the figure.

After utilizing data extraction, semantic modeling and integration of all the available process-related data, a wire harness assembly-specific knowledge graph makes it possible to perform RCA based on ontology reasoning, such as SWRL rules, using the implemented FTA in Figure 4 as base knowledge. Examples of SWRL rules to manage the decision support within several possible root causes, using the semantic approach are as follows:

- Detect a symptom with a certain analytic technique: $ProcessStep(?x) \wedge hasSymptom(?x,?y) \wedge isDetectedWith(?y,?z) \wedge Symptom(?y) \wedge$ **MeasurementTechniques**$(?z) \rightarrow isDetectedWith(?x,?z)$
- Find the location of the symptom in the complex system: $FaultMode(?x) \wedge FaultSymptom(?y) \wedge hasSymptom(?x,?y) \rightarrow FaultEquipment(?z) \wedge happenedAt(?x,?z)$
- Verify the possibility of operator related causes: $FaultMode(?x) \wedge Parameters(?y) \wedge FaultCharacteristics(?x,?y) \wedge System(?a) \wedge happenedAt(?x,?a) \wedge FaultMode(?z) \wedge SetpointCheck(?z,?x) \rightarrow causedBy(?x,?z) \wedge$ **ManpowerCause**$(?x) \rightarrow FALSE$
- Verify the possibility of a material related cause: $FaultMode(?x) \wedge Parameters(?y) \wedge FaultCharacteristics(?x,?y) \wedge System(?a) \wedge happenedAt(?x,?a) \wedge FaultMode(?z) \wedge SetpointCheck(?z,?x) \rightarrow causedBy(?x,?z) \wedge$ **MaterialCause**$(?x) \rightarrow TRUE$

The semantic annotations, object and data properties in reasoning rules can facilitate the data enrichment of the knowledge graph from FMEA and production process data aspects as well, such as *MeasurementTechniques*, *ManpowerCause* or *MaterialCause*.

An example of fault mode can be that the terminal does not fit properly into the fixture, which creates an increased time to perform the attachment activity. The result of the quality check of the crimping machine can show that the quality of the material is low in the case of the terminal. To give a more detailed summary, Table I represents a partial FMEA, related to the explained activity, which refers to a wire terminal attachment. The FMEA table shows further characteristics of the fault, such as Detectability, Occurrence, Severity and RPN (Risk Priority Number). The outcome of the analysis is the recommended action and the response, which can be applied in the production process. In case of the wrong material cause (second row of the table) the response action to eliminate the fault is to change the terminal in the first step of the process, which can be performed without reconfiguration of the workstation or assembly process. A recommended action is to create a warning message on the crimping machine display if such a fault mode occurs again, which can be performed with a survival analysis, that estimates the machine setup and changeover times in a crimping machine [33].

Implementing the extracted data into the knowledge graph provides access to interlinked data discovery or the so-called cross-domain reasoning. Figure 5 gives a semantic network visualisation example (low quality related cause of FMEA Table I), of how the proposed ontology-based framework utilizes

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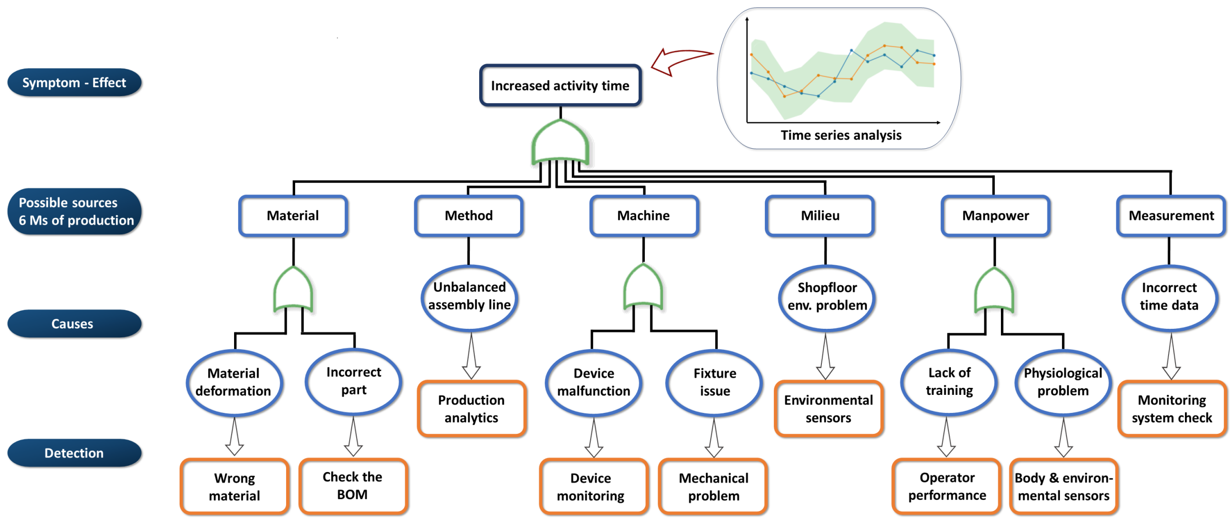

Fig. 4. Fault tree analysis of the investigated increased activity time phenomenon in a wire harness assembly process

TABLE I
PARTIAL FMEA OF A WIRE HARNESS ASSEMBLY ACTIVITY

Process	Mode	Effect	Sev.	Cause	Occ.	Current controls		Det.	RPN	Rec. act.	Response
						Prevention	Detection				
Attachment of a wire terminal	Terminal does not fit into the fixture	Increased activity time	4	Low-quality material - wrong terminal	8	Quality check of crimping machine	Visual inspection by the crimping operator	6	192	Warning message on the crimping machine display	Terminal change in the first step of the process
				Aged fixture	5	Quality check of fixture	Visual inspection	7	140	Warning message	Fixture repair or change
				Human workforce factor	3	Timed resting stops	Body sensor check	5	60	Monitoring of body signals	Operator reallocation

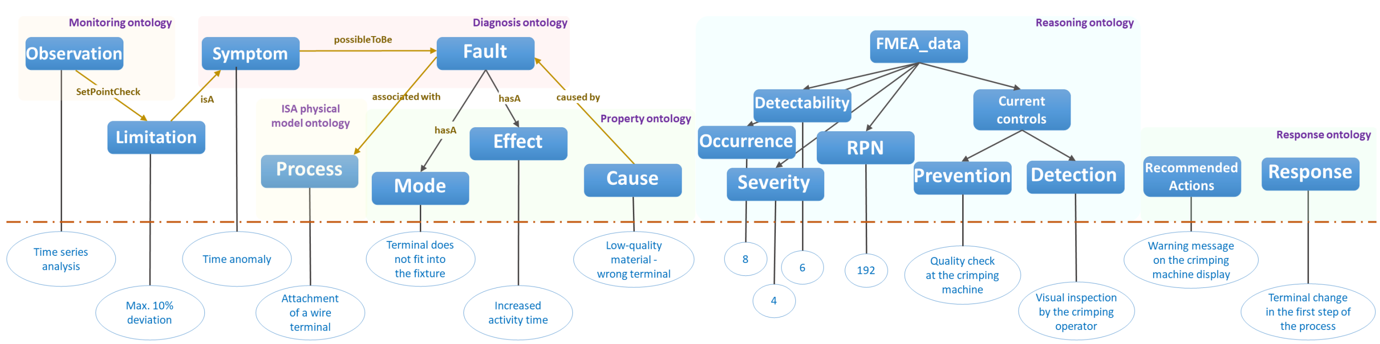

Fig. 5. Ontology-based semantic data representation of a fault cause diagnosis regarding to a wire harness assembly activity

the information about the detected wire harness assembly-related fault. The top side of the visualisation shows the ontology classes, where the information is stored in a machine-readable way in different sub-ontologies, while the bottom side of the figure shows the attributes of this specific fault instance. Additional information is denoted with yellow arrows regarding the fault, as to which process is it associated with and what caused it.

To automate a system response (a result of the analysis) i.e. a survival analysis-based estimation method can be implemented in the reasoning segment of the framework, which enables to perform the recommended action automatically, while the time-stamped machine data is transformed into the knowledge graph.

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Additionally, a further outcome of the semantic-based data management is that the response answer such as recommended actions, dashboard information or production data analytics can be received about the the diagnosed fault. As a classical FMEA supports the creation of a control plan for a complex production process, the proposed methodology aims to support the CI/CD (Continuous Integration and Continuous Delivery) best practice.

V. Conclusions

This paper investigated the field of fault detection and diagnosis in Industry 4.0 aspects and studied ontology-based methods for model-based analysis, such as integration of fault tree analysis, ontology-based reasoning and root cause analysis. Based on the state-of-the-art an ontology-based fault detection and diagnosis framework has been proposed, which combines diagnosis techniques, fault tree analysis, ontology rules, semantic annotation and reasoning. Additionally, a wire harness assembly process-based example has been presented to perform fault detection, using the knowledge graph, FMEA data and the FTA-based ontology reasoning.

Future work will focus on developing the detailed knowledge graph and testing the proposed framework on industrial case studies, including the integration of real FMEA, HAZOP and process data into the knowledge graph. Furthermore, problem-specific semantic annotation and ontology-based reasoning algorithms are planned to be developed.

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