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Dependability Modeling for the Failure Prognostics in Smart Manufacturing

David N. LIRA[1] and Milton BORSATO
Federal University of Technology – Parana, Av. Sete de Setembro 3165, Curitiba, PR 80230-901, Brazil

Abstract. The recent advances in Smart Manufacturing open opportunities in Maintenance and Management of its assets through new support strategies. This trend allows the collection of machine operation data in the shop floor, in order to interact with cyberspace computers through a communication network, therefore enabling the Cyber Physical System concept (CPS). Furthermore, the rapid advances of Information and Communications Technology (ICT) provide means to analyze Big Data, more quickly, autonomously, ubiquitously and in real time, offering information that assist in more efficient decision making in manufacturing processes. Nowadays, Prognostic and Health Management (PHM) leverages researches in the new generation of manufacturing. For this, an architecture called 5Cs, that directs the PHM implementation in CPS context is being adopted with expressive results, which allows the application of several math and/or Artificial Intelligence techniques to estimate the assets' remaining useful life. In particular, the use of Experts Systems and semantic information modeling can make it possible to represent knowledge found in the scientific literature and consolidated standards about the subject. This paper uses methodology of ontology development 101, which guides management, development and documenting of a formal taxonomy of failure prognostics. For model creation and evaluation, the Protégé suite is used, for it allows future researches to interact with the model, such as monitoring techniques and failure diagnostics in order to simulate real cases of mechanical components. This way, new possibilities for cyberspace oriented application development for industrial machine health management are revealed.

Keywords. Cyber Physical System, Prognostic and Health Management, Smart Manufacturing, Ontology Engineering, Expert Systems.

Introduction

In the new industrial generation, Cyber-Physical Systems (CPS) represent the interaction between physical spaces (sensors, actuators, mobile devices, RFID technology, embedded systems and others still) and cyberspace (computing and logical algorithms). That interaction must be ubiquitous and in real time through the internet, creating the Industrial Internet of Things (IIoT) [1], where the transit of Big Data [2] is made possible.

CPS has several applications in communication, transport, energy, infrastructure, health, public security, civil, military, robotic and disasters attendance fields. In the field of manufacturing, it improves operation process performance, monitoring and

[1] Corresponding Author. Tel.: +55-42-3141-6867; mobile: +55-42-98701462; e-mail: nunez@utfpr.edu.br

control, developing and implementing measurement techniques, reasoning and planning, promoting collaborative and cognitive systems, which aims increasingly the inclusion of human being with computational ambient or cyberspace [3].

Manufacturing in the CPS context requires Big Data analytics for generation useful information towards plenary understanding of systems, subsystems and their complexes interactions. According to Gao et al [4] a promising CPS application in the Smart Manufacturing context is Prognostics and Health Management (PHM), pointing out as an emerging approach of Mechanical Engineer to improve men-machine interaction through specific methods that helps to understand the machine behavior and assist to make more efficient decisions [5].

When PHM is unfold, the resulting prognosis may lead to condition monitoring in addition to events such as failure diagnostics [6]. Depending on which kind of data is needed to describe the system of interest and predict its future behavior, prognosis techniques can be classify as [4, 6, 7] physical models and data-driven approaches to estimate Remaining Useful Life (RUL) of a given asset. In particular, data-driven approaches use extracted information from historical data for establishing a relationship between nominal behavior and real time states of an operation machine, by applying either static techniques of Artificial Intelligence (AI).

On the other hand, the Health Management share refers to decision-making supplied by Prognosis through Condition-Based Maintenance (CBM), for carrying out appropriate recovery intervention or repair [4]. Between Prognostics and Health Management, the Prognostics is regarded the key-process of PHM [8]. In this context, AI techniques associated to Expert Systems (ES), based in professional knowledge representation of a particular area [9], are promising. Thereby, scientists have developed ontologies for knowledge representation, which allow interpretations of computer through taxonomies that can assist in inaccurate system function identification[10].

In Manufacturing, PHM has had good results when used in rotating elements, such as well as bearing, gears, shaft, impeller, pulley, fans, pumps, turbines, compressors, generators, electrical engine and blowers [5]. However, in the early phases of PHM development it is necessary the use to analysis techniques for dependability, which is the best way of ensure effective machine functioning in a given industrial process.

On Esmaeilian et al. [11], one of the most accepted architectures for orientating PHM implementation as CPS in the Smart Manufacturing is proposed by [12]. It details PHM into 5 levels called 5Cs: Connection, Conversion, Cyber, Cognition and Configure. The present paper further develops knowledge in data Conversion.

1. Theoretical Background

Two topics were considered essential for creating the model definition: dependability and methods for ontology engineering. Such concepts and fundamentals bring together the necessary expertise for prognostics modeling.

1.1. Dependability in factories and its attributes

According to Bukowski [13] dependability can be applied to all technology development subjects. Based in IEC 60050-192 [14] standard, dependability of an item is deemed to be the ability to perform, a function, as and when required considering attributes of availability, reliability, recoverability, maintainability and maintenance support performance.

Regarding to prognostics, dependability analysis may potentially lead to better monitoring of components in order to ensure high productivity [13].

1.2. Threats to dependability

In process of dependability acquisition, there are threats that may influence the proper life cycle functioning of manufacturing systems, either in development stage (conception) or in use stage (operation) [15]. Those threats, which may affect dependability of an item, can be considered Failure, Error or Fault.

1.2.1. Failure

Failure, according to IEC 60050-192 [14], is the loss of ability of a component to perform a required function. The failure of a component is an event that results in a system fault. According to Avižienis et al. [16], all failures that may affect a system during its life are classified as: creation, boundaries, cause, dimension, objective, intent, capability and persistence. The present paper discusses failure that can happen in a mechanical component (physical failures), resulting from a human action (human-made failures).

1.2.2. Fault

Fault, according to IEC 60050-192 [14], is the incapacity of a system to perform its required functions due the functioning deviation of an internal state. Fault in a system results from a component failure in its own system or a disability in an earlier stage of its life cycle, such as specification, design, manufacture or maintenance.
In the present study, faults that may be detected, classified in the detectability category, according to events through which the fault presence becomes evident [14].

1.2.3. Error

Error, according to IEC 60050-192 [14], is the discrepancy between a computed, observed or measured value or condition, and the true, specified or theoretically correct value or condition. Therefore, a procedure that guides the correct choice of technique, mechanism or device used to monitor the component behavior is necessary.

1.3. Means to attain dependability

The means to achieve dependability, may be categorized as: Failure Prevention, Failure Tolerance, Failure Removal and Failure Prognostics [16]. Failure prevention and failure tolerance aim to provide the ability to deliver an operation that can be trusted, while failure removal and failure prognostics aim to reach confidence in that ability by justifying that the functional and the dependability specifications are adequate and that the system is likely to meet them.

Thereby, the present work aims focus in failure prognostics as a way to estimate RUL in a given mechanical component.

1.4. Dependability analysis techniques

According to IEC 60300-3-1 [17], there are several techniques that assist in failure prognostics, such as: Failure Tree Analysis (FTA), Failure Mode, Effects and Criticality Analysis (FMEA), Markov analysis, Hazard and Operability study (HAZOP), Petri Net (PN) and Reliability Block Diagrams (RBD) [18].

Vogl, Weiss and Donmez [19] suggest that dependability techniques may be classifies into top-down and button-up approaches. On Sanislav et al. [18], they can be divided according to its quantitative and qualitative purpose. In addition, the dependability analysis techniques that can assist in the extraction of cause-effect relationship might be classified into deductive or inductive.

Those authors highlight FMEA uses for dependability analysis as it is: (a) a qualitative technique for identifying component failure modes; and (b) inductive, because it aims the prognostics of potential failures effects from known causes and for being a bottom-up approach, which first identifies failure modes in components, then establishes its effects.

1.4.1. Failure Mode and Effect Analysis

FMEA is a powerful technique used by engineers and reliability analysts to identify functions and components in which failure will lead to unwanted results, such as production loss, damage or even accidents. The main FMEA purpose is to find out and prioritize failure modes potentials through Risk Priority Number (RPN) estimate that represent a negative effect on the system and its proper functioning [20].

FMEA added to Criticality Analyses is called FMECA. Nowadays, the scientific literature considers FMECA and FMEA synonyms, since both identify failure modes, their effects, causes and prioritize its relevance through RPN, which is the multiplication of obtained values in Severity, Occurrence and Detection [20].

The FMEA development must gather technical knowledge, such as standards and scientific articles, and this knowledge can be modeled through ontology for several applications. Some FMEA applications in manufacture processes using ontology are present in Zhao and Zhu [21].

In order to find the RPN, it is important to standardize scoring parameters. Thereby, the SAE J1739 standard [22] establishes parameters to: specify severity of a given failure mode, occurrence for a cause or source cause, and finally presenting a classification scale for the probability of failure or cause mode, for detection and/or prevention of a cause occurrence in an existing control or system scheduling.

2. Ontology engineering

According to Aljumaili et al. [23], the term ontology refers to the philosophy that concerns the nature and reality structure. Therefore, ontology engineering focuses on nature and structure of things, regardless of its actual existence. In computing, specifically in the AI area, ontology building is the technique that represents the formal knowledge of a specific interest domain that is shared by a group of people. In some manufacturing solutions, the interopeability desired for operating data, used for strategic decision-making can be ruled by specific standards through ontology uses.

When creating an ontology, it is important to adopt a methodology for arranging and defining the construction stages. According to Bautista-Zambrana [24], methodologies for building ontologies involve a set of activities such as, conceptualisation, formalization, implementation and maintenance. Some highlighted methodologies are: Uschold and King's, METHONTOLOGY, On-To-Knowledge, TOVE, OntoClean, DILIGENT, Ontology Development 101 and DOGMA.

Besides of methodologies, ontology engineering requires tools that support all development activities. Commercial tools, such as TopBraid and OntoStudio are available, as well as free options, such as OntoEdit, Hozo and Protégé. Among those tools, are highlighted those that are not owned, and which have plug-in extensibility, along with import and export capabilities in XML (S), OWL, RDF (S) and Excel formats, as well as graphical views. The Protégé editor stands out for meeting those requirements.

Protégé is the most used tool for editing ontologies in the scientific world [25, 26]. It is developed and maintained by Stanford University, which is also aligned with Ontology Development 101. The present work uses Protégé as a modeling tool and Ontology Development 101 as the construction approach, as proposed by Natalya and Deborah [27], and illustrated in Figure 1.

Figure 1. Stages suggested according to methodology 101, adapted from [27].

3. Case study

3.1. Failures in mechanical components

The component used in the case study is a bearing that has the function to reduce wear on the operating shaft of a centrifugal ventilator. Part of the interaction of its failure modes are represented by an ontology that formalizes its dependability analysis through FMEA technique. Table 1 highlights the factors to be modeled for the failure mode "bearing seized", having the "overheat" effect, rated severity "8" caused by "insufficient lubricant", rated occurrence "5" with "training" as a preventive control, "vibration analysis" as detection control and rated detection "8". Ontology prognostics is modeled considering those characteristics in terms of having obtained the highest RPN, which is 320.

Table 1. FMEA partial for failure prognostics modeling.

Item/ Function	Failure Mode	Failure Effect	SEV	Possible Cause	OCC	Current Control: Prevent	Current Control: Detect	DET	RPN
Bearing / Reduce friction of the rotating shaft	Bearing seized	Overheat	8	Incorrect type of lubricant	1	-	-	8	64
				wrong procedure of lubrication	1	-	-	10	80
				insufficient lubricant	5	Training	Vibration Analysis	8	320

I. Determine scope

The ontology domin is failure prognostics, which is a way to achieve dependability in manufacturing machines. An ontology can be built to identify failure modes in the mechanical component, "bearing". An important aspect when identifying failure modes is that there is a dependency of threat types that will rank their nature for future analysis. This ontology called OntoProg, maintained by the research group GECVP from UTFPR, can be used in various types of industrial process machinery.

II. Consider reuse

With the establishment of the scope of ontology, it could be used as a reference to ontologies developed in [18].

III. Enumerate terms

Several terms were considered for this ontology related to the threats of dependability as the FMEA technique, such as cause, effect, occurrence, severity, failure, defect, error, etc. For this step to be standardized the terms and their meanings were collected from consolidated standards and scientific articles, related to equipment dependability.

IV. Define Classes

DependabilityAnalysis is the main class of the proposed ontology and contains subclass FailurePrognostics as a way of reaching prognostics, which in turn has subclasses Threats and FMEA. Each of these classes has its own subclasses. For example, subclass Threats has subclasses: Failure, Fault and Error. The subordination relationship between class and subclass is a 'subClassOf' axiom type. The 'DisjointWith' axiom type relationship exists between classes, so that the instance contained in it can not be an instance of more than one of the involved classes. For example, Failure is DisjointWith Fault and Error. So Fault is automatically DisjointWith Failure and Error and Error is DisjointWith Fault and Failure. The class hierarchy is presented in Figure 2.

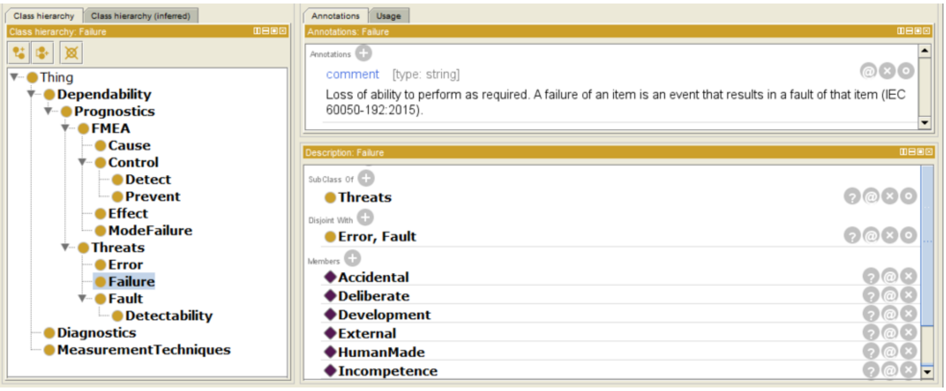

Figure 2. Classes hierarchy in OntoProg ontology.

V. Define properties

There are three types of properties: ‘Object Property’, that establishes a relationship between two ontology classes, ‘Data Property’, which lists the classes with different data types and ‘Annotation Properties’, which enables adding information to classes, instances (objects) and even other types of properties. Below are detailed properties and their corresponding Ranges. Figure 3 shows properties of the classes in Protégé: Object Properties: hasCause (Cause), hasControl (Control), hasEffect (Effect), hasMode (ModeFailure), isResultedOf (Failure) and isCausedBy (Failure); Data Property – hasDetection (integer), hasOccurence (integer), hasSeverity (integer).

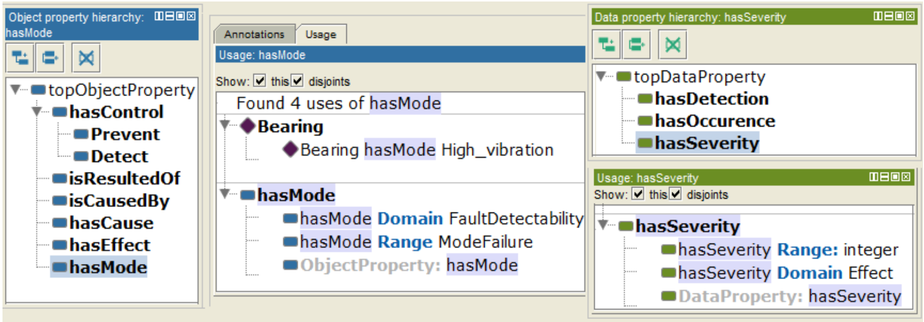

Figure 3. Proprieties in OntoProg.

VI. Define constraints

At this stage transitive properties are defined. For example, if instance "Bearing" hasCaused an instance of the class Cause and this cause isResultOf an instance of Failure class then the instance "Bearing" isResultOf an instance of the class Failure. Therefore, inferences of type the "Bearing" also isResultedOf of Accidental, NonDeliberate Incompetence and NonMalicious failures can be performed, as shown in Figure 4.

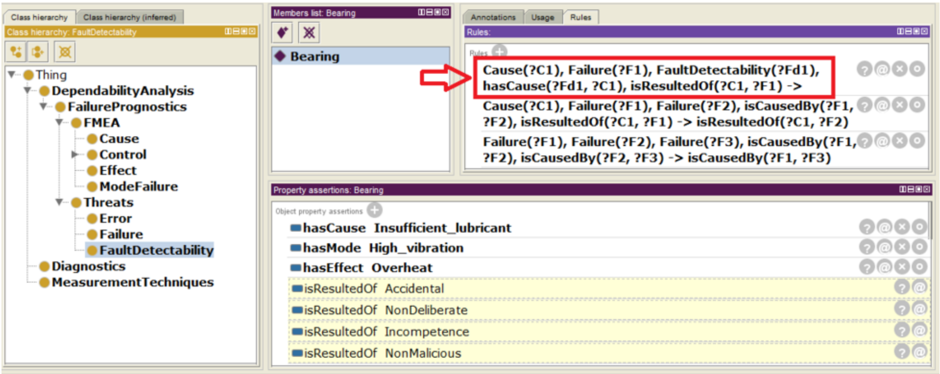

Figure 4. Transitive restrictions for generating instances in in OntoProg.

VII. Create instances

Instances are designed to: Cause, Control, Effect, Modefailure, Failure and FaultDetectability. Figure 5 presents instances of Failure Class. In this connection, it can be seen that the purple color arrows refer to subClassOf property, blue arrows are Types properties, and orange dashed arrows are the isCausedBy object properties.

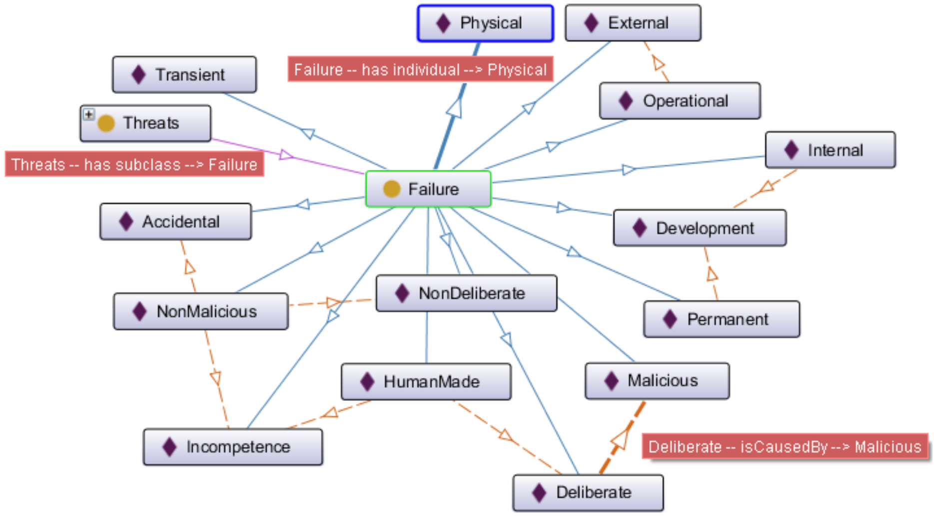

Figure 5. Instances of Class Failure in OntoProg ontology.

4. Testing and Results

The proposed model of dependability analysis can be interpreted, accessed and updated in real time by cyberspace for some applications in failure prognostics. For this, the model must be tested first. This is possible with SPARQL that performs query ontology language (SPARQL Protocol and RDF Query Language) for being the most used form [28].

Protégé provides an editor to create SPARQL queries. In it, it uses utfpr prefix to connect with the dependability analysis model called untitle-ontology-111, Figure 6.

That way, the query in the SPARQL OntoProg ontology can be used to find, for example, within class Failure, all X instances that have isCausedBy Y property, as shown in Figure 6. These results can be used by software applications through APIs, such as Jena Semantic Web Toolkit and Jena Fuseki.

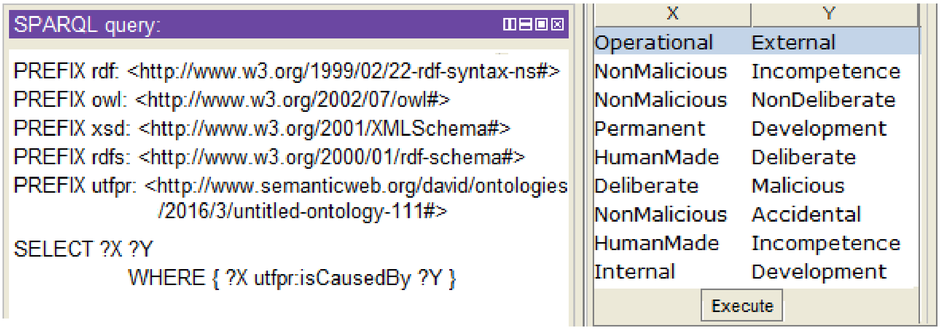

Figure 6. Failure Class instances in Protégé.

5. Final remarks and future work

This paper deals with CPS scientific challenges related to the development of new PHM models , including threat identificating methods (Failure, Fault and Error). In addition, this article seeks to establish the theoretical foundations for dependability modeling of failure prognostics in the CPS context. In this regard, the article proposes a methodology to ensure the PHM dependability, by suggesting a model to adapt in a dynamic and evolving context in cyberspace. The methodology uses the FMEA technique as dependability analysis and Ontology Development 101, built upon seven stages.

The model is implemented in Protégé and all the necessary steps for their generation were detailed. In addition, tests were carried out through queries in SPARQL, which show that the model can be used by other applications in the CPS context, highlighting its scalability and usability.

The model integration methods for determining failure diagnostics and condition monitoring techniques within the PHM context will be subject of future work.

References

[1] L. Wang, M. Törngren and M. Onori, Current status and advancement of cyber-physical systems in manufacturing, *Journal of Manufacturing Systems*, Vol. 37, 2015, Part 2, pp. 517-527.

[2] M.A. Pisching, F. Junqueira, D.J. Santos Filho, P.E. Miyagi, Service Composition in the Cloud-Based Manufacturing Focused on the Industry 4.0, *Technological Innovation for Cloud-Based Engineering Systems*, 2015, pp. 65-72.

[3] D. Gorecky, M. Schmitt, M. Loskyll and D. Zuhlke Human-machine-interaction in the industry 4.0 era, *12th IEEE International Conference on IndustrialInformatics (INDIN)*, 2014, pp. 289-294.

[4] R. Gao, L. Wang, R. Teti, D. Dornfeld, S. Kumara and M. Mori, Cloud-enabled prognosis for manufacturing, *CIRP Annals - Manufacturing Technology*, Vol. 64, 2015, pp. 749-772.

[5] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao and D. Siegel, Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications, *Mechanical Systems and Signal Processing*, Vol. 42, 2014, pp. 314-334.

[6] S.T. Kandukuri, A. Klausen, H.R. Karimi and K.G. Robbersmyr, A review of diagnostics and prognostics of low-speed machinery towards wind turbine farm-level health management, *Renewable and Sustainable Energy Reviews*, Vol. 53, 2016, pp. 697-708.

[7] A. Ragab, M.-S. Ouali, S. Yacout and H. Osman, Remaining useful life prediction using prognostic methodology based on logical analysis of data and Kaplan–Meier estimation, *Journal of Intelligent Manufacturing*, 2014, pp. 1-16.

[8] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Péra and N. Zerhouni, Degradations analysis and aging modeling for health assessment and prognostics of PEMFC, *Reliability Engineering & System Safety*, Vol. 148, 2016, pp. 78-95.

[9] B. Scholz-Reiter, M. Kück and D. Lappe, Prediction of customer demands for production planning – Automated selection and configuration of suitable prediction methods, *CIRP Annals - Manufacturing Technology*, Vol. 63, 2014, pp. 417-420.

[10] Y.H. Yin, A.Y.C. Nee, S.K. Ong, J.Y. Zhu, P.H. Gu and L.J. Chen, Automating design with intelligent human–machine integration, *CIRP Annals - Manufacturing Technology*, Vol. 64, 2015, pp. 655-677.

[11] B. Esmaeilian, S. Behdad and B. Wang, The evolution and future of manufacturing: A review, *Journal of Manufacturing Systems*, Vol. 39, 2016, pp. 79-100.

[12] J. Lee, H.D. Ardakani, S. Yang and B. Bagheri, Industrial Big Data Analytics and Cyber-physical Systems for Future Maintenance & Service Innovation, *Procedia CIRP*, Vol. 38, 2015, pp. 3-7.

[13] L. Bukowski, System of systems dependability – Theoretical models and applications examples, *Reliability Engineering & System Safety*, Vol. 151, 2016, pp. 76-92.

[14] International Electrotechnical Commission, *IEC 60050-192: International Electrotechnical Vocabulary -Part 192: Dependability*, 2015.

[15] W. Elghazel, J. Bahi, C. Guyeux, M. Hakem, K. Medjaher and N. Zerhouni, Dependability of wireless sensor networks for industrial prognostics and health management, *Computers in Industry*, Vol. 68, 2015, pp. 1-15.

[16] A. Avižienis, J.-C. Laprie, B. Randell and C. Landwehr, Basic concepts and taxonomy of dependable and secure computing, *IEEE Transactions on Dependable and Secure Computing*, 2004, No.1, pp. 11-33.

[17] International Electrotechnical Commission, *IEC-60300-3-1: Dependability Management-Part 3-1: Application guide - Analysis techniques for dependability - Guide on methodology*, 2003.

[18] T. Sanislav, G. Mois and L. Miclea, An approach to model dependability of cyber-physical systems, *Microprocessors and Microsystems*, Vol. 41, 2016, pp. 67-76.

[19] G.W. Vogl, B.A. Weiss and M.A. Donmez, Standards for Prognostics and Health Management (PHM) Techniques within Manufacturing Operations, *Annual Conference of the Prognostics and Health Management Society*, September. 2014.

[20] V. Ebrahimipour, K. Rezaie and S. Shokravi, An ontology approach to support FMEA studies, *Expert Systems with Applications*, Vol. 37, 2010, pp. 671-677.

[21] X. Zhao and Y. Zhu Research of FMEA Knowledge Sharing Method Based on Ontology and the Application in Manufacturing Process, *2010 2nd International Workshop on Database Technology and Applications*, 2010, pp. 1-4.

[22] Society of Automotive Engineers, *SAE J1739: Potential Failure Mode and Effects Analysis in Design (Design FMEA) and Potential Failure Mode and Effects Analysis in Manufacturing and Assembly Processes (Process FMEA) and Effects Analysis for Machinery (Machinery FMEA)*, 2009.

[23] M. Aljumaili, K. Wandt, R. Karim and P. Tretten, eMaintenance ontologies for data quality support, *Journal of Quality in Maintenance Engineering*, Vol. 21, 2015, pp. 358-374.

[24] M.R. Bautista-Zambrana, Methodologies to Build Ontologies for Terminological Purposes, Procedia - Social and Behavioral Sciences, Vol. 173, 2015, pp. 264-269.

[25] M. Graube, J. Pfeffer, J. Ziegler and L. Urbas, Linked Data as Integrating Technology for Industrial Data, *2011 14th International Conference on Network-Based Information Systems (NBiS)*, 2011, pp. 162-167.

[26] L.F. Lin, W.Y. Zhang, Y.C. Lou, C.Y. Chu and M. Cai, Developing manufacturing ontologies for knowledge reuse in distributed manufacturing environment, *International Journal of Production Research*, Vol. 49, 2011, pp. 343-359.

[27] F.N. Natalya and L. Deborah, *Ontology development 101: a guide to creating your first ontology*, Stantford Medical Informatics Technical Report, SMI-2001-0880, 2001.

[28] World Wide Web Consortium (W3C), *SPARQL 1.1 Federated Query*, 2013. Available: https://www.w3.org/TR/2013/REC-sparql11-query-20130321/: Accessed: 20-Abr-2016.