A priori indicator identification to support predictive maintenance: application to machine tool

Thomas Laloix[1,2], Hai Canh Vu[1], Alexandre Voisin[1], Eric Romagne[2], Benoît Iung[1]

[1] *Université de Lorraine, CNRS, CRAN, F-54000 Nancy, France*

thomas.laloix@univ-lorraine.fr
hai-canh.vu@univ-lorraine.fr
alexandre.voisin@univ-lorraine.fr
benoit.iung@univ-lorraine.fr

[2] *Usine Renault Cléon, BP 105, 76410 Cléon, France*

thomas.laloix@renault.com
eric.romagne@renault.com

ABSTRACT

Predictive maintenance requires the identification of the parameters to be monitored and sensors to be implemented on a system. In industrial companies, usually such goal is tackled by implementing sensor and after see if one can extract some indicators related to degradation. The lack of methodology makes the benefits of predictive maintenance to be lower than expected. Indeed, its implementation is done by "the rule of the thumb" using some metrics "a posteriori" in order to show the relevancy of the instrumentation. Hence, a structured approach is required in order to define "a priori" the most suitable indicators to be relevant for degradation monitoring and related instrumentation to be implemented. Thus, the paper presents a methodology based on a coupled approach of FMECA and Hazard Operability analysis (HAZOP) which aim is to contribute to the deployment of predictive maintenance strategies by clearly identify pertinent indicator. This approach is based on the formalization of concepts of knowledge which permit to constitute the first pillars of predictive maintenance approach. The formalization step leads to promote meta-model and reference model of knowledge. The feasibility and the interests of such approach are shown on the case of machine tool GROB G520 located in RENAULT Cléon Factory. It consists in particularizing the reference model proposed to identify automatically and in a more efficient the right indicators/parameters on which the predictive maintenance of this machine tool should be based.

1. INTRODUCTION

In industrial companies, predictive maintenance aims at forecasting process degradation or process deviations to perform maintenance action just in time allowing to anticipate process/asset failure. It avoids costly downtime, reduces maintenance costs and transforms "unplanned stops" to "planned ones" for a more efficient production optimization (Roy, Stark, Tracht, Takata, & Mori, 2016). In that way, predictive maintenance is based on parameter monitoring related to asset, process or product conditions. These parameters are linked to degradation mode assessment in order to create health indicators. The evolution of these health indicators can be then determined by a prognostic process to provide remaining useful life (RUL) parameter usable to take adequate decision with regards to process/product future changes. This vision of predictive maintenance is those expected in Renault factories such as Cleon one in the way to move from "fail and fix" maintenance strategies to "predict and prevent" ones.

Nevertheless, existing approaches does not completely fulfill the industrial need starting with the definition of relevant parameters to be monitored and indicators elaboration for degradation monitoring up to the deployment of a solution which could be used in a huge number of production systems. Hence, a relevant challenge is to propose a structured approach, dedicated to industrial application, for the definition and development of pertinent indicators on which the predictive maintenance is founded (Laloix, Iung, Voisin, & Romagne, 2016).

To face this challenge, the paper proposes a knowledge meta-modeling integrating functioning/dysfunctioning concepts as well as causality relationships to model the degradation progress into the system. This meta-modelling based on UML (Unified Modeling Language) will be the core from which an advanced and efficient predictive maintenance can be constructed for providing relevant indicators as inputs to decision-making process. Thus the originality of this proposal is (a) to formalize all the knowledge concepts, their attributes and their relationships for supporting the link between degradation at different system abstraction level in consistence with specialized well-known approaches, (b) to offer, by means of the meta-model, a high degree of genericity allowing to use it for several industrial application classes, and finally (c) to provide to Renault, for the machining center application class, a reference model (obtained by meta-model instantiation) to promote predictive maintenance policies on this application class.

Regarding this originality, the section 2 introduces the problem statement on indicator definition from relevant monitoring parameters. It leads to isolate limits of these current approaches. In section 3, we propose a meta-model based on functional and dysfunctional concept of knowledge. This meta-model is instantiated in section 4 to create a reference model for the application class of machining center. Then, the relevance of the meta-model and the reference model are shown, in section 5, on linear axis subsystems of the GROB BZ560 machining center implemented in Cleon factory. This application highlights the need of methodology for industrial companies to identify and select relevant parameters to be monitored for manufacturing system health assessment. Finally, section 6 proposes some conclusions and perspectives.

2. PROBLEM STATEMENT ON INDICATOR DEFINITION IN THE FRAME OF PREDICTIVE MAINTENANCE

Development of predictive maintenance strategies implies for decision makers to possess indicators representing asset degradation. These indicators are considered as a snapshot of the system condition/degradation in comparison to a reference, considering various aspects such as performances, environment etc. (Rizzolo, Abichou, Voisin, & Kosayyer, 2011). An important issue, in manufacturing context, is the identification of parameters to be monitored on the asset and the elaboration of the degradation indicators. Moreover, such approaches have to consider industrial deployment aspect, so being able of genericity and scalability.

Several methods based on dysfunctional analysis (e.g. identification of degradation modes) are already operational (Renu et al., 2016). For example, in relation to degradation knowledge, (Catelani et al., 2015) identified monitoring parameters for each dysfunctional mechanism in case of failure mode. In the same way, (Atamuradov, Medjaher, Dersin, Lamoureux, & Zerhouni, 2017) proposed such analysis to determine parameters to monitor. It corresponds to the first step of a global 4th steps methodology dedicated to ease the implementation of predictive maintenance strategies in industry. The first consists in critical component analysis bringing the second, the selection of appropriate sensor for condition monitoring. The third represents the prognostics feature evaluation under data analysis and finally, the fourth, the prognostics methodology and tool evaluation matrices derived from predictive maintenance literature. (Tiddens, Braaksma, & Tinga, 2018) proposed to examine economic and technical factors to select the suitable component to monitor, after the reduction of candidate by criticality classification. (Verl, Heisel, Walther, & Maier, 2009) estimated process degradation thanks to wear parameters monitoring and (Efthymiou, Papakostas, Mourtzis, & Chryssolouris, 2012) has formalized this monitoring process in predictive maintenance framework from knowledge management. About predictive maintenance indicator, (Mourtzis, Vlachou, Milas, & Xanthopoulos, 2016) proposed fusion of sensing information based on process information and operators reports. Even if monitoring parameters are identified and indicators determined, they are limited to a specific application class of process.

To face the genericity and scalability issues, some approaches already exists. For example, (Iung, Medina-Oliva, Weber, & Levrat, 2012) combine functional and dysfunctional concepts of knowledge supported by Probabilistic Relational Model (PRM). The concepts are extracted from FMEA (Failure Mode and Effect Analysis) and HAZOP (Hazard and Operability study) methods. Nevertheless, it does not consider the monitoring parameter identification and thus sensing strategy. On the same basis of FMEA study, (Renu et al., 2016) identify the impact of process degradation on product quality through a knowledge based system. The genericity and scalability is ensured by knowledge based FMEA approach. In the same way, (Rehman & Kifor, 2016) propose a reusable and scalable tool based on ontology to support FMEA knowledge. Also, (Candea, Kifor, & Constantinescu, 2014) face this issue by the proposition of case-based reasoning approach. The proposed knowledge system is supported by FMEA-driven software and is deployed on a manufacturing context. Nevertheless, each of these approaches does not identify sensing solution in the purpose to constitute indicators as input of decision making process.

Thus, the existing approaches are not fully satisfactory leading to promote a challenge for a structured approach based on the identification of relevant monitoring parameters to constitute and provide indicators in the predictive maintenance framework in industrial context (Laloix et al., 2017).

3. PROPOSAL OF A META-MODEL TO SUPPORT INDICATOR DEFINITION

To face with the previous issue, the contribution proposed aims at developing a meta-model formalizing all the generic knowledge concepts, their attributes and their rules required to identify relevant parameters to monitor for the elaboration of health indicators. This formalization, based on UML (MEGA tool) is integrating:

- Knowledge concepts of process functional analysis to identify the basic items on which the meta-model is constructed,
- Knowledge concepts of process dysfunctional analysis to identify, from relevant FMEA and HAZOP methods, the items to support causality from degradation to deviation (Laloix *et al.*, 2017)
- Knowledge concepts to support extension of these two methods to finalize the link between causality principle and the health indicator item.

3.1. Knowledge concepts of functional analysis

The functional modeling of an industrial process consists most of the time, in formalizing, by qualitative causal relationships, the interactions between the functions performed at each level of the process until the elementary level (elementary functions). In that way, this modelling can be supported by tool such as SADT (Structured Analysis and Design Technique) in which semantic rules can be added in consistent with system theory principles (Medina-Oliva, Iung, Barberá, Viveros, & Ruin, 2012). Thus, the analysis corresponds to a process decomposition in functions and sub-functions until elementary functions supported by technological mechanism. The global function is associated to the global system (higher level of abstraction), and each function is associated to a sub-system until the component level. A system owns specific attributes such as its name, its class, its type … Each (sub)function achieves finality. It consumes Input flows and produces Output flows materializing, in sense of system theory, knowledge related to the finality, the know-how, the energies, the resources, the information … (Medina-Oliva et al., 2012).

Each flow is characterized by a quantity of objects per unit of time, and each flow and object are characterized by properties (e.g. weight, length for the final part being one object among the flow of produced parts). Functions are linked through the chain of input/output flows allowing to propagate the effect of function/sub-system degradation. A part of the UML formalization of the previous concepts, attributes and relationships is shown in Figure 1-A.

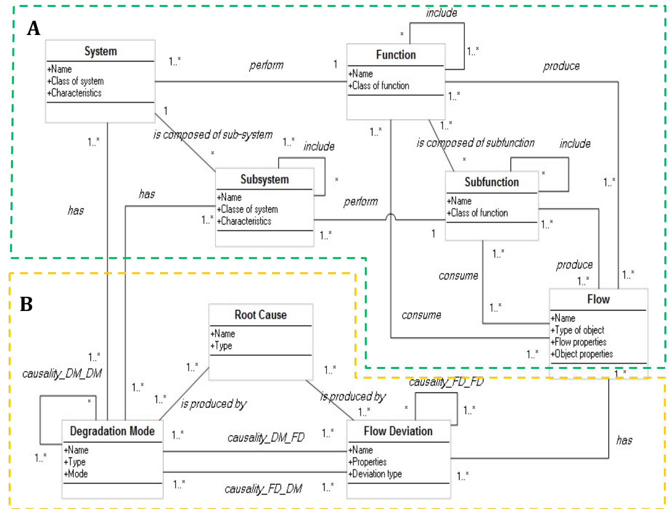


Figure 1. Extract of the meta-model related to functional (A) and dysfunctional (B) knowledge concepts

3.2. Knowledge concepts of dysfunctional analysis

From the concepts of system, function, and flow, related to functional aspect, it is now necessary to study dysfunctional one. Dysfunctional analysis is done by considering concepts of approved FMEA and HAZOP methods knowing that FMEA is oriented toward technical aspects (machine, component) and leads to the identification of degradation and failure mode, while HAZOP is focused on flow deviation.

Knowledge concepts introduced by FMEA method represent identification of failure modes and degradation ones (in the frame of predictive maintenance) attached to each system/sub-system level. Root causes which generate such failure or degradation are identified as well as the system consequences, and the detection means (Candea et al., 2014). Quantification of the impacts on the system finality is also evaluated. In complementary way, HAZOP method is introducing knowledge concepts such as flow and properties deviations (e.g. less, more) in regards with function/sub-functions, and consumed/produced flows. Criticality of flow deviation consequences is also evaluated. Root causes are identified, as well as detection means.

Association between these concepts of degradation mode and flow/property deviation is a first step on linking the product/process joint consideration. It is formalized by causality relationship (Figure 1-B). Moreover, the notion of criticality is added to the meta-model through quantification of the relationships. It represents the importance of degradation mode or deviation mode on the process and is evaluated by ranking criteria. This ranking appears on degradation mode (DM) and flow deviation (FD) relationships attributes. In compliance with causality relationship, a flow deviation can trigger another flow deviation (causality_FD_FD), but also another degradation mode (causality_FD_MD). As well as a degradation mode can entail other degradation mode (causality_DM_DM) or flow deviation (causality_DM_FD).

3.3. Knowledge concepts of FMEA and HAZOP knowledge extension

3.3.1. Monitoring parameters

The strategy to identify the monitoring parameters is directly issued from functional and dysfunctional causality relationship. Thus, monitoring parameters can be both focused on the performance associated to the function and its deviation or on the degradation/failure mode related to the component. Furthermore, this causality formalizes a real link between degradation mode and flow deviation. In general, the monitoring of a particular failure/degradation mode can be mainly related to: (a) the degradation mechanism itself, (b) the causes of the degradation and (c) the effects of the degradation mode. In relation to this monitoring, parameters can focus on degradation for (b), physical mechanism for (a) and flow property measurement for (b) and (c). Consequently, monitoring parameters represent either the symptoms of the degradation (e.g. temperature, vibrations), the system performance (via output flow properties) and resulting effects on upstream or downstream degradation mechanism or function properties (e.g. torque rise, output reduction). Formalized relationship between classes related to these concept of knowledge is illustrated Figure 2.

3.3.2. Health indicators elaboration

From the identification and selection of monitoring parameters, health indicators are elaborated with more semantics (at different abstraction levels). Indeed, health indicator is mainly defined as an aggregated index assessing a current global state in comparison to a nominal one, considering various aspects such as performances, on-going degradation, environment etc. (Rizzolo et al., 2011). So, the elaboration process is: elaboration of degradation indicators based on the analysis and normalization of the failure mode monitoring parameters, elaboration of performance indicators based on the analysis and normalization of monitoring parameters related to system performance; then, combination/aggregation of the 2 former classes of indicators to get the (system/subsystem) health indicators by considering also the process parameters (e.g. type of product, tool n°, program n°).

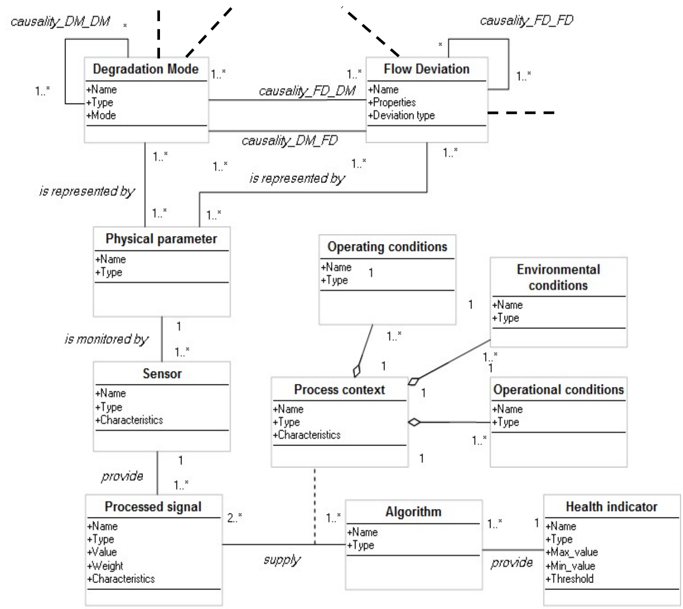


Figure 2. Extract of the meta-model related to FMEA and HAZOP extensions (complementary part of Figure 1)

Thus, the current global meta-model is composed of all the necessary concepts, attributes and relationships to generate health indicators of combined process/product consideration. As this meta-model is fully generic and very conceptual, it was decided, in the frame of Renault, to generate (by instantiation procedure), reference models more adapted and usable for different classes of machine/systems encountered in Renault factories. The first one was performed for the machining center application class.

4. REFERENCE MODEL DEFINITION FOR MACHINING CENTER APPLICATION CLASS

The machining center reference model (an extract is presented Figure 3) has to contain all the knowledge expected to be exploited for identifying relevant parameters to monitor in the way to implement predictive maintenance for this category of machine. The reference model is created from instantiation of all meta-model items (e.g. concepts). This results in a high capacity of model portability from a machining center case to another. Indeed, machining center share the same upper abstract level subsystems such as electro spindle, axis, etc. Only when the level comes to technical ones, the models significantly differ.

Instantiation procedure (made also on MEGA tool) starts by creating, from *system* class, a class *machining center*. Machining center function corresponds to *transform part*, and represents an instance of *function* class. A system can only perform one function, whereas a function can be performed by different systems. For instance, the only finality of machining center is *to transform part*, but this later can also correspond to the finality of stamping press.

Machining center function consumes and produces *flows*. Related instantiated input flows are *raw part*, *cutting tool*, *energies*, and output flows are *transformed part* and *metal removal*. *System* class is composed by 0 to n subsystem classes. Instantiation of *subsystem* class leads to create, at least, *linear axis*, *rotational axis*, *electro spindle unit* and *tool change unit* classes. Each of these machining center subsystems performs a function corresponding to *sub-function* class instantiation leading respectively to the following: *to displace cutting tool*, *to rotate work piece*, *to rotate cutting tool*, *to provide new tool*. Then the instantiation procedure is continued by the identification of degradation mode and flow deviation related to technological aspect and associated flows (and their attributes). Finally, the operation is performed until defining the occurrences of the *health indicator* class (and also the related attributes).

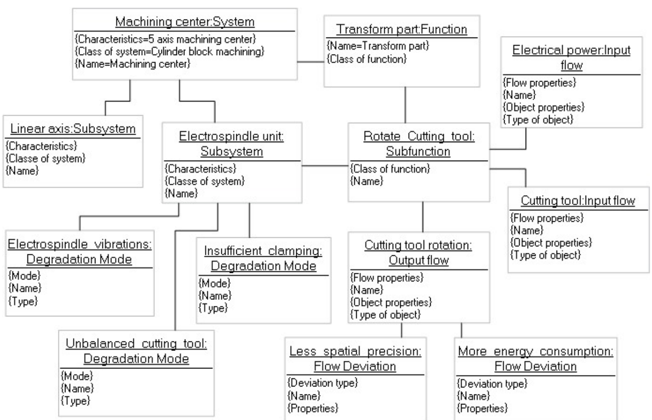


Figure 3. Extract of the machining center reference model

Thus, the machining center reference model is elaborated to be the common generic model able to serve for the whole diversity of machining centers inside and/or outside Renault context.

5. PARTICULARIZATION OF THE MACHINING CENTER REFERENCE MODEL TO GROB BZ560 MACHINING CENTER

This reference model has been used and validated in the Renault Cleon Factory for the case of the specific GROB BZ560 machining center (a 5 axis, dual-spindle). It constitutes a first step for implementing an advanced predictive maintenance on this machine knowing that the development of this specific model results from a particularization of the reference model. A focus has been done on the modelling of linear axis subsystems (Figure 4) to identify relevant indicators to be monitored. These later are parallel axis Z1 and Z2 involved in the spindle linear displacement (and so cutting tool linear displacement) used to machine the work piece. These axis play a central role in the machining process, ensuring spindle maintaining or displacement during machining operation according to machining operation type (drilling, milling, boring). Both axis Z1 and Z2 realize the same operations/process and when one is not operational (cutting tool breakage, lack of work piece…), the other does not run.

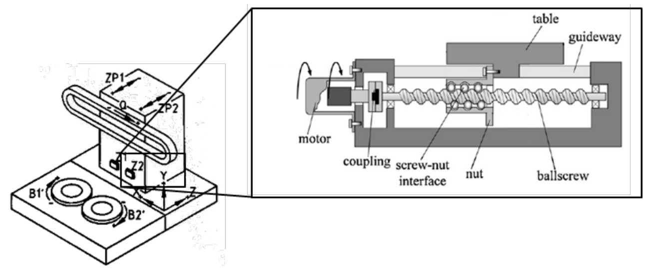


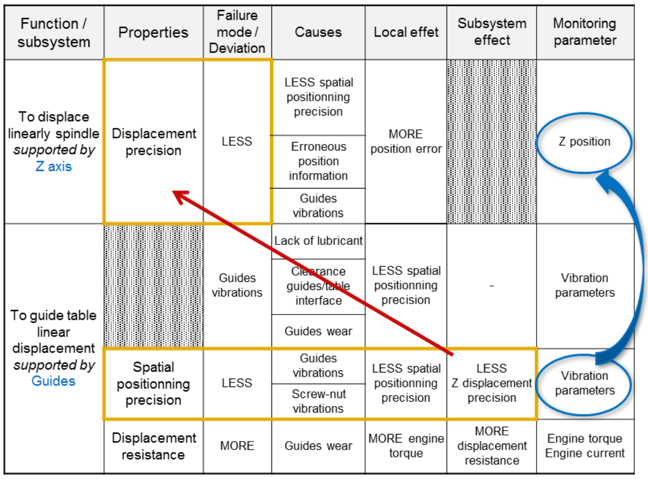
Figure 4. GROB BZ560 kinematic (linear axis Z1 and Z2 (Altintas, Verl, Brecher, Uriarte, & Pritschow, 2011))

5.1. GROB BZ560 functional and dysfunctional analysis

Linear axis is an occurrence of machining center subsystem class. It performs the cutting tool displacement through the displacement of the table where is fixed the spindle (*function: to displace linearly spindle*). It is controlled by *process orders* (position requirements), consumes *electrical power*, and produces *cutting tool linear displacement* and *position information*. Linear axis function is decomposed into several elementary functions such as (i) *to transform electrical energy into rotational mechanical energy*, (ii) *to transmit motor shaft rotation to ballscrew*, (iii) *to guide ballscrew rotational movement*, (iv) *to transform ballscrew rotational movement into table linear displacement*, (v) *to monitor table position* and (iv) *to guide table linear displacement*. Each of these elementary functions is respectively supported by (i) *electrical motor*, (ii) *coupling*, (iii) *bearings*, (iv) *nut,* (v) *sensors* and (vi) *guides*.

Focusing on the function *to guide table linear displacement*, input flow is *table linear displacement* (output flow of the function *to transform ballscrew rotational movement into table linear displacement*), characterized by position and time properties. The output flow is represented by *guided displacement*, characterized by spatial positioning precision and guiding resistance properties.

Based on the functional analysis, dysfunctional analysis can be performed. In that way, for each component (e.g. *guides*), related failure modes are identified (e.g. *guides vibrations*) as well as output flow properties deviation (e.g. *less spatial positioning precision*, *more displacement resistance*.). Then, the causes are developed in link with the component state and the deviation of the input flow properties. For instance, *guides vibration* main causes can correspond to lack of lubricant, clearance between guides and table, pollution, or guides wear). It leads to isolate output flow properties deviations (e.g. *less spatial positioning precision*), but also the potential impacts on the output flow properties of upstream function (e.g. *more engine torque* related to the function *to transform electrical energy into rotational* *mechanical energy*). All this knowledge is easily implemented and updated by maintenance expert towards graphical interfaces, on the basis of general system knowledge provided by the reference model (Figure 5). These interfaces are informational forms created directly from the processes associated with the meta-model and reference model (e.g. processes related to the relation-ships, the occurrences).



Function / subsystem	Properties	Failure mode / Deviation	Causes	Local effet	Subsystem effect	Monitoring parameter
To displace linearly spindle *supported by* Z axis	Displacement precision	LESS	LESS spatial positionning precision Erroneous position information Guides vibrations	MORE position error		Z position
To guide table linear displacement *supported by* Guides		Guides vibrations	Lack of lubricant Clearance guides/table interface Guides wear	LESS spatial positionning precision	-	Vibration parameters
	Spatial positionning precision	LESS	Guides vibrations Screw-nut vibrations	LESS spatial positionning precision	LESS Z displacement precision	Vibration parameters
	Displacement resistance	MORE	Guides wear	MORE engine torque	MORE displacement resistance	Engine torque Engine current

Figure 5. User interface dedicated to FMEA/HAZOP concepts used by maintenance team to implement specific machine database

Finally, guides degradation materialized by *spatial positioning precision* output flow property leads to upper abstraction level impact towards the deviation of *displacement precision*. The resulting effect corresponds to the increase of *position error*.

From the identification of such flow property deviation, the definition of health indicator can be addressed, considering the monitoring parameters and industrial context (operational condition, environmental condition, etc.; See Figure 2).

5.2. GROB BZ560 relevant indictor to support predictive maintenance

Indeed, from functional and dysfunctional instantiated knowledge (results of the step explained in previous section), it is then necessary to identify the representing physical parameter, the sensing solution, the signal processing, to consider process context and finally define health indicator elaboration.

Regarding *position error*, the related *physical parameter* corresponds to *axis position.* Related *sensor* solution and *signal processing* are internally managed by machining center. Indeed, this information is necessary for its functional needs. The corresponding process context represents for instance *work piece diversity 1* and *work piece diversity 2* (e.g. diversity means different types of cylinder block). Associated *algorithm* to achieve the position error deviation monitoring represents *position error algorithm*. Position error e(k) is equal to the difference between the real position xr(k) and targeted position x(k) at each control interval (k) (Altintas et al., 2011). Finally, position error e(k) value is cumulated by cycle. *Cumulated position error per cycle* corresponds to a relevant *health indicator* for Z1 and Z2 axis. Such indicator has been calculated for Z1 axis and Z2 axis on two months datasets (representing 1500 machining cycles), considering two diversities (*diversity 1* and *diversity 2*) of machined part. The obtained results are depicted in Figure 6 and Figure 7. The comparison between both distribution highlights an early deviation of Z2 axis indicator in comparison with Z1 axis. Indeed, distribution of Z1 axis is centered on a single value, and mean and wide are considered as nominal state, whereas Z2 axis indicator distribution appears bi-modal.

Concerning *less positioning precision* related to *Z1 axis guides* and *Z2 axis guides* dysfunctional aspects, a corresponding *physical parameter* is *vibration*. This later is monitored by *sensors* such as *accelerometers* located on Z1 and Z2 guides. *Accelerometers* provides *radial vibration acceleration* information, corresponding to *processed signal*. The relevance of such signal is ensured by the consideration of *process context* (i.e. *cutting tool rotation speed, cutting tool lifetime, work piece diversity*). Finally, based on *processed signal* and *process context*, *health indicator* is elaborated. It represents both Z1 guides and Z2 guides temporal signals during machining phase, filtered on cutting tool rotation frequency to remove noise (i.e. *vibration indicators*). Both axes work in the same process conditions and their cutting tools have the same lifetime. The *vibration indicators* are presented Figure 5. It reveals that amplitude of acceleration signal of Z2 axis is more important than Z1 axis, meaning that Z2 axis guide stability is more degraded than Z1 axis.

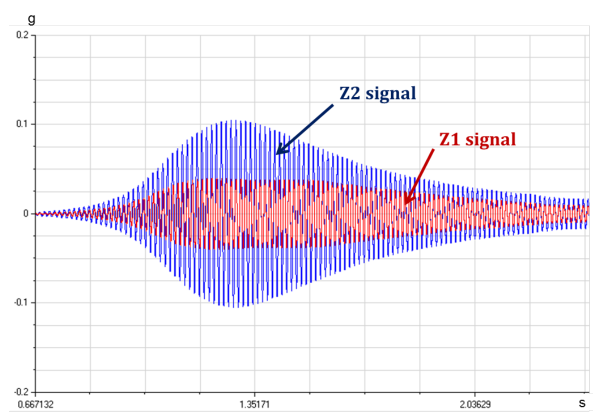


Figure 5. Z1 axis and Z2 axis vibration indicator

Each degradation mode or flow deviation is being able to be monitored, either by their causes, or by the degradation modes or flow deviations themselves or by the resulting effects. Based on causality relationship identified through the dysfunctional analysis, sensing strategy can be operated at component level, or subsystem level according to the desire level of precision.

The degradation is monitored by two different ways. First, the occurrence of linear axis degradation is observed by component degradation monitoring (i.e. guides degradation). The advantage is the ability to detect early degradation mechanism and to directly focus on the degrading component. Nevertheless, in industrial context, monitoring the component level of manufacturing systems is not economically relevant. A solution can be the monitoring of the degradation at subsystem level through a subsystem degradation indicator. This corresponds for linear axis to position error indicator. A deviation of such indicator means a degradation of axis positioning precision. However, monitoring of this type of indicator does not indicate the degrading component.

To overcome this limit, a solution is the fusion of indicators merging information coming from both component and subsystem degradation.

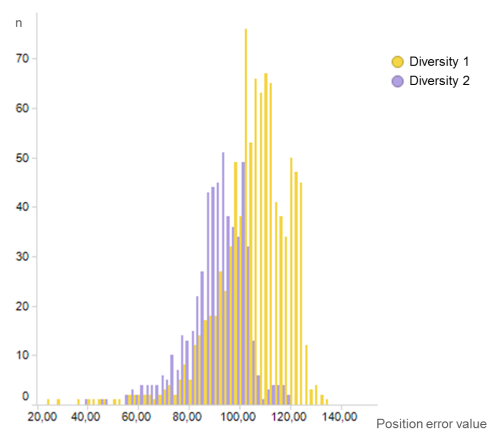


Figure 6. Z1 axis position error distribution

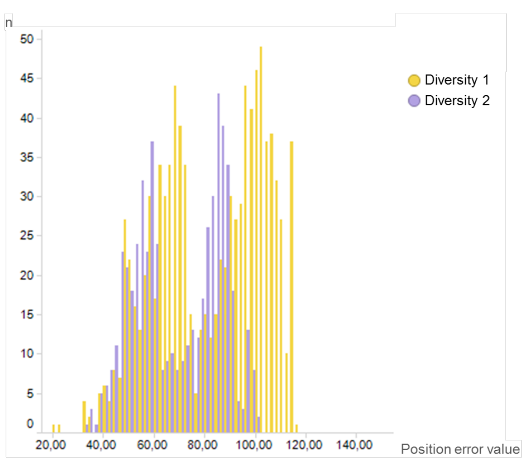


Figure 7. Z2 axis position error distribution

6. CONCLUSION

The paper proposed an UML-based meta-model formalizing all concepts of knowledge required to support definition of pertinent indicators to be monitored for implementing advanced predictive maintenance in manufacturing industry. More precisely, the concepts are representative of functional/dysfunctional analysis, and extension of the FMEA and HAZOP methods. This meta-model has been instantiated to the class of machining center to offer Renault with a generic basis of knowledge potentially usable for different kind of machines. In that way, a particularization of the reference model has been done to specific GROB BZ560 machining center and more specifically to the linear axis sub-system. The particularization step showed the feasibility and relevance of the reference model to aid in the definition of degradation indicators in a very consistent way. The work in progress is the development of the reference model for all the machining center but also the development of other reference models in relation to other Renault classes of manufacturing systems.

Future work will be the definition and implementation of algorithms to aggregate degradation indicators, leading to the construction of a global health index and finally monitoring the system and sub-system health.

REFERENCES

Altintas, Y., Verl, A., Brecher, C., Uriarte, L., & Pritschow, G. (2011). Machine tool feed drives. *CIRP Annals - Manufacturing Technology*, *60*(2), 779–796.

Atamuradov, V., Medjaher, K., Dersin, P., Lamoureux, B., & Zerhouni, N. (2017). Prognostics and Health Management for Maintenance Practitioners -Review, Implementation and Tools Evaluation. *International Journal of Prognostics and Health Management*, (3), 2153–2648.

Candea, G., Kifor, S., & Constantinescu, C. (2014). Usage of case-based reasoning in FMEA-driven software. *Procedia CIRP*, *25*(C), 93–99.

Catelani, M., Ciani, L., Cristaldi, L., Faifer, M., Lazzaroni, M., & Khalil, M. (2015). Toward a new definition of FMECA approach. *Conference Record - IEEE Instrumentation and Measurement Technology Conference*, *2015–July*, 981–986.

Efthymiou, K., Papakostas, N., Mourtzis, D., & Chryssolouris, G. (2012). On a Predictive Maintenance Platform for Production Systems, *3*, 221–226.

Iung, B., Medina-Oliva, G., Weber, P., & Levrat, E. (2012). Using probabilistic relational models for knowledge representation of production systems: A new approach to assessing maintenance strategies. *CIRP Annals - Manufacturing Technology*, *61*(1), 419–422.

Laloix, T., Iung, B., Voisin, A., & Romagne, E. (2016). Towards the control of product quality from the process deviation monitoring: Overview and investigation in automotive sector. *IFAC-PapersOnLine*, *49*(28), 79–84.

Laloix, T., Voisin, A., Deeb, S., Romagne, E., Iung, B., & Lorange, F. (2017). Industrial system functioning/dysfunctioning-based approach for indicator identification to support proactive maintenance. *IFAC-PapersOnLine*, *50*(1), 13704–13709.

Medina-Oliva, G., Iung, B., Barberá, L., Viveros, P., & Ruin, T. (2012, June 25). Root cause analysis to identify physical causes. *11th International Probabilistic Safety Assessment and Management Conference and The Annual European Safety and Reliability Conference, PSAM11 - ESREL 2012*.

Mourtzis, D., Vlachou, E., Milas, N., & Xanthopoulos, N. (2016). A Cloud-based Approach for Maintenance of Machine Tools and Equipment Based on Shop-floor Monitoring. *Procedia CIRP*, *41*, 655–660.

Rehman, Z., & Kifor, C. V. (2016). An Ontology to Support Semantic Management of FMEA Knowledge, *11*(August), 507–521.

Renu, R., Visotsky, D., Knackstedt, S., Mocko, G., Summers, J. D., & Schulte, J. (2016). A Knowledge Based FMEA to Support Identification and Management of Vehicle Flexible Component Issues. *Procedia CIRP*, *44*, 157–162.

Rizzolo, L., Abichou, B., Voisin, A., & Kosayyer, N. (2011). Aggregation of Health Assessment Indicators of Industrial Systems. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11*(July), 1007–1014.

Roy, R., Stark, R., Tracht, K., Takata, S., & Mori, M. (2016). Continuous maintenance and the future–Foundations and technological challenges. *CIRP Annals-Manufacturing*, *65*, 667–688.

Tiddens, W., Braaksma, J., & Tinga, T. (2018). Selecting Suitable Candidates for Predictive Maintenance. *International Journal of Prognostics and Health Management*, *Vol. 9*, *No*(May), 1–14.

Verl, A., Heisel, U., Walther, M., & Maier, D. (2009). Sensorless automated condition monitoring for the control of the predictive maintenance of machine tools. *CIRP Annals - Manufacturing Technology*, *58*(1), 375–378.