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PROGNOSTIC DESIGN: REQUIREMENTS AND TOOLS

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Abstract:

Maintenance plays now a critical role in manufacturing for achieving important cost savings and competitive advantage while preserving product conditions. It suggests moving from conventional maintenance practices to predictive strategy. Indeed the maintenance action has to be done at the right time based on the system health state and component Remaining Useful Life (RUL) assessed by a prognostic process. But this new process needs methodology to support its design phase. Thereby when requirements about the expected quality of prognostic results are made, questions about the selection of addressed failure modes and of their prognostic model/tool appear. Thus this paper faces with challenges by proposing a methodology enabling to guide the designer for answering the previous questions. This methodology describes tools needed to formalize the necessary system functional and dysfunctional knowledge and gives guidelines allowing to design prognostic process with the respect of expected requirements.

Keywords:

Prognostic – Maintenance – Design methodology.

1. INTRODUCTION AND PROBLEM STATEMENT

Even if maintenance is a necessity, maintenance has a negative image and suffers from a deficiency of understanding and respect. It is usually recognised as a cost, a necessary evil, not as a contributor. Moreover traditionally the scope of maintenance activities has been limited to the production vs. operation phase. But as the paradigm of manufacturing shift towards realizing a sustainable society, the role of maintenance has to change to take into account a life-cycle management oriented approach [11] for enhancing the eco-efficiency of the product life [3]. In that way, maintenance has to be considered not only in production vs. operation phase but also in product design, product disassembly, and product recycling … [11] and has to be lead the implementation of a set of means and processes for acting on the operational requirements to carry out the global system performances [1].

To support this new role in operation, the maintenance concept undergone through several major developments to lead to proactive considerations which require changes in transforming traditional “fail and fix” maintenance practices to “condition-based vs. predictive” strategies performed only when a certain level of component degradation (impacting profit/product conditions) occurs [4]. The business processes the most important to develop anticipation action are monitoring, diagnosis, prognosis and decision-making processes. Among these modules, the prognosis process is often considered as the main one while its goal is fundamental for implementing anticipation capabilities.

Indeed, prognosis has to predict the future health of the system and generate the different RULs (Remaining Useful Life of the system, part of the system or component) for each detected (current) or potential degradation/failure mode, by taking into account the knowledge of the system (functional and dysfunctional), past information (background), current information (current state) and future information (scenario with manufacturing and maintenance data) [13].

Thus prognostic is a process dealing with a lot of knowledge (more or less formalized) which is issued from different sources. The identification and the use of this knowledge needed all along the prognostic life cycle, and particularly in the engineering phase, require a consistent methodology for guarantying and validating, at the end, requirements about prognostic results quality.

About methodology, [6] notice that most of the developed prognostics approaches are application or equipment specific and that a generic and scalable prognostic methodology does not exist. Moreover [12] shows that a huge number of paper tackling the prognostic issues present a lack of common methodology. Among the methodologies presented, any one allows to obtain a global reasoning for the prognostic design phase. The authors propose only some items to be followed in the design phase but without real consistency between the items:

- Establish the requirement of the system
- Perform a failure mode analysis
- Determine the most critical failure mode
- Determine the available model in order to prognosticate these failure modes taking into account sensor capabilities
- Assess the obtained model with metrics about accuracy, precision and robustness.

Nevertheless [8] propose a more complete methodology. It uses the functional and dysfunctional analyses of the system to define its structure and health. Stochastic processes are also formalized for supporting the degradation dynamic. The use of common analyses is relevant but the *a priori* choice of the technology/tool (Bayesian network) limits the application cases.

Therefore a generic methodology for prognostic design is still missing leading to answer to the following questions:

- What are the failures modes to be anticipated for the system?
- What are the technologies/tools/models to be used to support this anticipation?

These questions are generic but their answers depend on the context in relation to the life phase of the system and the available knowledge. Indeed the system could already exist or could currently be designed. The amount of system knowledge differs if system components are specific or not to the application or if their model is new or well-known. This issue request the inventory of the prerequisites needed for prognostic engineering.

To face this challenge, this paper proposes a generic methodology for selecting the failure modes (e.g. the most critical) needing prognostic and its technology/tool associated to reach the prognostic requirements in terms of result quality. To reach its goal, the methodology is supported by an analysis gathering the necessary knowledge for prognostic engineering.

The relation between the system life phase and the prognostic design phase is addressed in section 2. Then section 3 describes the proposed methodology for selecting failure modes and associated prognostic tools. Section 4 delivers some conclusion and perspectives.

2. PROGNOSTIC DESIGN AND SYSTEME LIFE CYCLE

For the system engineering point of view (in relation with INCOSE initiative[1]) the principal system is the system performing the global function and needs contributor processes for supporting it in operation phase. These last processes represent the support system whose supply chain and maintenance are the main processes. Maintenance enables system of interest to fulfill its finality by deploying strategies which could evolve during the principal system life.

The strategic decision to move to proactive maintenance can be made at different moment of the system life. This decision implies to design and build an integrated system of proactive maintenance as described in [13] and thus its key process named prognostic. The context for the prognostic engineering depends on the system life phase when prognostic is engineered. During the system design phase, the physical part of the system does not exist. New paradigms promote the evaluation and simulation of the system into its different future environments in order to assess their impacts on the future system. This impact assessment could lead to (re-)design the system and in this case, maintenance issues and in particular prognostic issues and requirements could directly influence the system design. This way improve the global economical performance of system by decreasing the number of failures or their impacts on system finality (better reliability) and also by make easier the monitoring of the degradation modes and their forecasting and thus improve prognostic performances and decrease prognostic engineering time (and therefore its cost).

The decision to evolve could be made also when the system exists and operates. In this case the system is already built, thus modifications are difficult and expensive and the proactive maintenance aims at replacing a conventional strategy (corrective, timed-based, condition-based…) already performed on the system. The potential physical changes in the system are the integration of additional sensors. Thus the context is locked and the only lever to improve the global economic performance is the proactive maintenance design and above all the prognostic engineering. But the advantage, in comparison with the previous case, is the potential available knowledge which can be used to build prognostic models. The experience defined through expertise or data brings lots of information about the most frequent failure modes and is able to focus the prognostic engineering on them. This paper is interested by this case which does not authorize modification on the system it-self. Nevertheless some of proposal of this paper can be considered for both cases.

The design phase is the most important one because the other phase depends on it. Thus the prognostic engineering phase needs attention and has to follow a systems development model as the V-Model [10]. Therefore requirements and specifications about expected prognostic results have to be defined in first and represent the "system level design requirements" (figure 1). This phase is performed in two steps: (1) the choice of metrics for evaluating performance of the prognostic process and (2) the quantification of the expected level of these metrics. Lots of metrics are already proposed in the scientific contribution and address different points of view. But no methodology has been proposed for selecting the appropriate metrics. [9] give however a classification of the metrics and reviews the main ones. Thus the use of several metrics seems necessary to assess the different points of view (e.g. accuracy and precision). When the decision on metrics is planned out, the quantification of them is given and become requirements for the prognostic designer. A well-done requirement establishment phase allows to make easier integration and validation phases.

[1] http://www.incose.org/

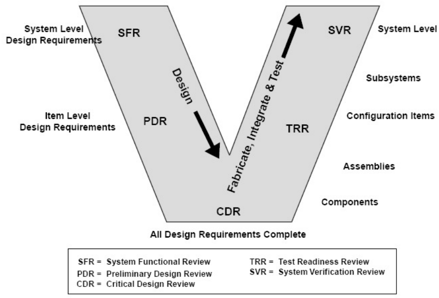

Figure 1: systems development model: V-Model [10]

Then the "Items level design requirements" can be started. It allows to determine the system structure and the component requirements. In the prognostic case, failure mode can be seen as "prognostic component". Then prognostic "Items level design requirements" phase aims at answering to the question addressing the choice of the failure modes according the system performances and of their supported technologies/tools/models needed to fulfill requirements.

3. PROGNOSTIC DESIGN: METHODOLOGY FOR SELECTING FAILURE MODES AND ASSOCIATED PROGNOSTIC TOOLS

An industrial system has lots of ways of dysfunction with a lot of degradation and failure modes. But the frequency of occurrence, the impact on the performances and the generated corrective or preventive maintenance cost could be very different from a failure mode to another one. Thus a method for selecting them and their associated prognostic tool is necessary as shown in the figure 2.

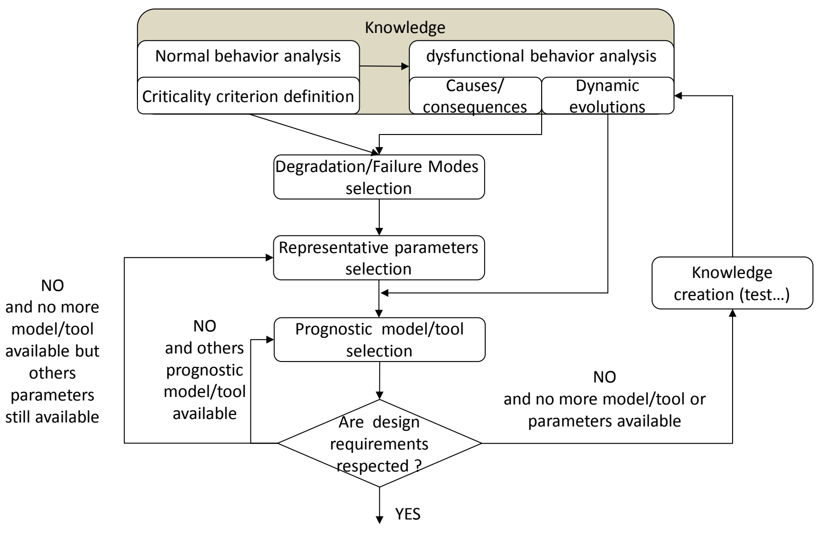

Figure 2: Methodology for selecting failure modes and prognostic tools

3.1. Normal behavior analysis

Designing contributor processes like prognostic need to know the principal system and its functioning way. A system is described by different points of view with specific models:

- Environmental point of view: description of the system environment and their interactions,
- Functional point of view: functional analysis (e.g. IDEF-0, FAST…), system model (e.g. transfer function),
- Operational point of view: control mode description (e.g. UML use case diagram),
- Organic point of view: description of the physical structure decomposed into sub-system until components), structure function, 3D representation (e.g. CAD software models),
- Technical point of view: technological description of the components, physical construction of the components,
- Management point of view: description of the economical data and of the policies and strategies deployed on the system and its parts for managing it along its all life.

From this last point come requirements for choosing the criterion used to classify the most important failure modes to prognosticate. On the figure 2 this criterion is called criticality criterion and characterizes the failure occurrence (e.g. cost, ecological impact, frequency, risk of no detection…).

3.2. Dysfunctional behavior analysis

Maintenance deals with the dysfunctional behaviors which need also methods and tools to represent and formalize the knowledge. Two kinds of knowledge could be distinguished: (1) the knowledge about causes and consequences and (2) knowledge about the evolution of degradation and failure phenomena. The first one is most of time described in a qualitative way. It is supported by a lot of tools whose the most popular are FMECA (Failure Mode, Effects, and Criticality Analysis), HAZOP (Hazard and operability study) or cause and consequence trees. The second kind of knowledge can be classified into several criteria:

- nature (probabilistic model as reliability model, based on physic law or on specific indicator evolution),
- quantitative or qualitative,
- the state space nature (discrete or continuous),
- static model description (probabilistic law (Weibull, exponential…), state definition of a discrete model as Markov chain…)
- dynamic model description (transition functions for discrete model, value of parameters…).

This dysfunctional knowledge is used for two reasons: to select failure modes and indicators and to build the prognostic model. The first one needs a global view of the available knowledge. Knowledge formalized with the form of table is easy to use but no method proposes to gather all the knowledge. [7] propose to extend the FMECA analysis with the degradation mechanism causes of failures. In that way we propose to use FMECA as an engineering tool for formalizing the knowledge (not as a method for analysing risk) and to complete it with information needed for selecting failure modes. Therefore the FMAP

(Failure Modes Analysis for Prognostic) is formalized into the table 1 composed of seven fields.

Failure Mode	Causes	Consequences	Criticality	Influential variables	Observable Indicators	Observable property

Table 1: FMAP (Failure Modes Analysis for Prognostic)

Failure mode, causes and consequences are the same field that their corresponding FMECA ones. They represent failure modes, their causes and their consequences. Criticality corresponds to the criterion defined by the management point of view in the normal behaviour analysis. Influential variables field allows to identify variables which affect the failure and/or the dynamic evolution of the degradation modes which cause it. These variables describe material/technological properties, operational mode and the environment variables which impact degradation/failure modes.

Observable indicators are raw or built signals on which degradation/failure modes can be observed. This or these indicator(s) allow(s) to identify if the degradation/failure mode has occurred (diagnostic) and the degradation level (health assessment). In the prognostic context, these indicators are projected and then used to compute RULs. Finally the last field is named observable property. This field has to be carry out for each observable indicators. This field answers at the question “what can we observe on the observable indicator evolution?”. Sometime only the failure or degradation is observable and sometime both are observable.

In the case of observable degradation, the dynamic between the degradation mode beginning and the failure occurrence could be more or less fast. Prognostic enables the anticipation of the failure for the purpose of (re-)scheduling a maintenance action. But a maintenance action needs a preparation time and if the RUL is too short, then the information for scheduling the preventive maintenance action happens too late and the action cannot be performed before the failure. Then the observable dynamic of the degradation mode (fast or slow) is important an information given in this field.

3.3. Degradation/Failure modes selection

After its formalization, the knowledge is used in first for selecting degradation/failure modes in order to focus on the most critical ones. Of course the first criterion is the criticality defined into the FMAP. But this criterion is not the only one because some critical degradation/failure modes could be not observable or could have no observable indicators able to be forecasted. In this case degradation/failure mode causes are considered and prognosticated. They need a function to pass from causes to subject mode (e.g. aggregation function). If one or more causes cannot also be prognosticated, the same way can be performed. But tools performing prognostic and aggregation are only models and thus insert incertitude and error sources in the final result. Therefore the choice of indicators which are representative of high-level degradation/failure modes (next of the critical mode) has to be preferred as often as possible.

3.4. Representative indicators selection

The prognostic of degradation/failure modes on component is supported by indicators forecasting. They could be representative for one or several modes and their evolutions characterize the degradation dynamic or the failure occurrence. These indicators can be measured directly on the system or built with aggregated data from other signals.

3.5. Prognostic model/tool selection

Prognostic models/tools operate the selected representative indicators forecasting by projecting it into the future. Their selections depend on the available knowledge about the evolution of degradation and failure phenomena that means about the indicators selected previously. Two sources provide knowledge: expertise and data. People who work sometime during several years in relation with a system collect a lot of information. This knowledge is most of time imprecise but brings a global view of the degradation phenomena. They enable also to fill in the lack of knowledge given by data. Well-known methods are used for formalizing this knowledge (FMECA, HAZOP…) and scientific contributions use also expertise like [14] for estimating parameters of proportional hazards model.

Knowledge from data brings more precision but most of time only on concise phenomena. Moreover the question about data quality can be asked: how is the measure precision? , are they complete or censured? , are data with noise? and so on. For using this knowledge lots of algorithms already exist to adjust model to the data (e.g. training algorithm for neural network, regression algorithm for linear, exponential or logarithm function…). The complementarity between both sources is important: the global knowledge but imprecise supported by expertise is able to be adjusted with a better precision using data and algorithm (for example the degradation law is given by the expert and its parameters adjusted by data).

The available knowledge is one of the main factors for selecting prognostic tool/model: either the more appropriate model is directly defined by the expert or the content and the format guide the selection. This link is highlighted by the classification of data based prognostic in [5]. This classification criterion used in this paper is the type of available information (traditional reliability approaches – event data based prediction, prognostics approaches – condition data based prediction and integrated approaches combining both approaches).

3.6. Requirements validation

The last phase of the methodology is the validation or not of the prognostic process in comparison with its expected requirements. When the prognostic quality is insufficient, i.e. when the required levels of the metrics chosen during the phase “system level design requirements” (figure 1) are not respected, a new selection of the prognostic model/tool has to be performed. This could concern a part or the totality of the representative indicators. The loop has to be repeated until reaching a sufficient result. Otherwise a new representative indicators selection could be performed in the same way. Then if the available knowledge is not sufficient to reach the prognostic design requirements, knowledge (data) has to be created by degradation test (run-to-failure test) or the integration of additional sensors.

4. CONCLUSION

This paper has proposed guidelines for prognostic design issues for a system currently in service. The main contribution is the proposal of a methodology for selecting degradation/failure modes and prognostic tools. This methodqology is supported by the functional and dysfunctional formalized knowledge enabling to classify each failure mode in relation to a specific criticality. This selection is related with a list of associated indicators to forecast and the knowledge about them leads to a choice of prognostic tool. If prognostic design requirements are not sufficient, selection and choice have to be reconsidered or knowledge has to be created by test or addition of sensors.

Method to choose more precisely the prognostic tool, adjust them and link together for reaching a global prognostic model is needed. The literature has lots of scientific contribution about component prognostic, but methodology and associated support tools for assessing future performance still missing. A first proposition has already made in [2] and could be continued and improved.

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