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A Cognitive Framework for Analysis and Treatment of Uncertainty in Prognostics

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Uncertainties exist in fault prognostics systems can lead to inaccurate results and this will lead to unnecessary or delay maintenance activities. The uncertainty must be considered carefully to achieve more effective engineering applications. Uncertainties have been classified as aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty is also called objective uncertainty, irreducible uncertainty, inherent uncertainty, and stochastic uncertainty. Epistemic uncertainty is also referred to as subjective uncertainty, reducible uncertainty and state-of-knowledge uncertainty. A cognitive framework to aid in the understanding of uncertainties and techniques for mitigating and even taking positive advantage of them is presented. From the perspective of man-machine-environment system engineering, the framework is an attempt to clarify the wide range of uncertainties that affect prognostics system. The uncertainty sources are identified as three aspects (machine, environment, man). A general uncertainty management procedure is proposed. It mainly contains uncertainty identification, qualification, propagation and sensitivity analysis. For case illustration purpose, the popular data-driven prognostics methods are discussed in detail. Current and developing methods for dealing with uncertainties are projected onto the framework to understand their relative roles and interactions.

1. Introduction

Prognostics is the process of predicting the future reliability of a product by assessing the extent of deviation or degradation of the product from its expected normal operating conditions (Pecht, 2008). Implementing prognostics can bring lots of benefits (Sun, 2012). Although the benefits of prognostics are impressive, prognostics technologies are still not mature enough for effective engineering applications. One of the major challenges for prognostics is the need to develop methods that are capable of handling real world uncertainties that lead to inaccurate predictions (Sun, 2012).

When the prognostics results are used to support the condition-based maintenance (CBM) decision, it is more important to consider the effects of the uncertainty sources on the predictive remaining useful life (RUL). The calculation of RUL alone does not provide sufficient information to form a decision or to determine corrective action. Without comprehending the corresponding measures of the uncertainty associated with the calculation, RUL projections have little practical value (Engel, 2000).

Some previous work has presented RUL results without any uncertainty measure (Celaya, 2012). Presently, research on prognostics has paid much attention on uncertainty analysis and treatment. Gu (2007) studied various sources of prognostic uncertainty. In their study, they utilized a sensitivity analysis to identify the dominant input variables that influence the model output. Orchard (2008) introduced a particle filtering based uncertainty representation and uncertainty management approach, in which the parameter uncertainty is the main object of the analysis. Besides, evaluating prognostic performance should also consider the uncertainty of the prediction results. Liu (2012) considered the uncertainties of the prognostics and the true data of the system when evaluating the online prognostics performance.

In order to guide the study of the prognostic technology incorporating the uncertainty management, this paper provides a cognitive framework for systematic identifying and analyzing the various sources of uncertainty. A general procedure of the uncertainty management is proposed. The general data-driven prognostics methods are analyzed in detail for the purpose of illustration.

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2. Cognitive framework of prognostics uncertainty

From the perspective of the man-machine-environment system engineering, the predicted system can be regarded as a **machine**, prognostics can be regarded as the process of the user (**man**) cognizing the changing of the fault states of the machine in certain **environment**, which means prognostics system is a complex man-machine-environment system. The interactive relationships between the three parts are as follows: human monitoring the parameters of the machine and environment, pre-processing the monitoring data and establishing the prognostics model to understand the predicted machine; further predicting the future fault state of the machine with the monitoring data and the prognostics models. The cognitive framework of prognostics uncertainty can be derived from the man-machine-environment perspective, as illustrated in Figure 1.

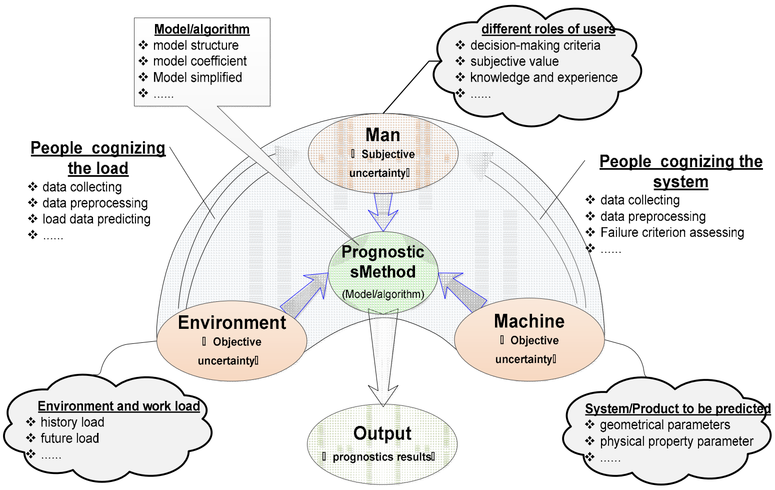

Figure 1: Cognitive framework of prognostics uncertainty

Uncertainty sources are the carriers of uncertainties, which exist in man-machine-environment system in static and dynamic forms. Uncertainty sources in static form refer to the geometric parameters, material physical properties of the predicted system and the load environment (environmental and work load). Such uncertainty sources refer to the inherent variation associated with the physical system and its environment. It is commonly called aleatory, variability, irreducible or stochastic uncertainty (Zio, 2009). It cannot be reduced with the improvement of human cognizing. This type of uncertainty is too large will lead to the future fault state of the predicted system can't be regard predictable. Uncertainty sources in dynamic form reflected in the process of people cognizing and treating the machine-environment system. This kind of uncertainty includes measurement errors, pre-processing errors, and cognition fuzziness of the failure criteria and approximation of the prognostic model structure. Figure 1 illustrates the static uncertainties lying in man, machine, load environment and prognostics method. It also point out that the dynamic uncertainties would generated when people cognize and treat the static uncertainties of the load environment and the predicted system (machine).

These uncertainty sources contain subjective and objective uncertainty because of people cognizing the machines with object uncertainty. Subjective uncertainty derives from some level of ignorance or incomplete information of the system or the surrounding environment (Cullen, 1999). Due to the limitation of human knowledge, data incompleteness, data unreliability or information fuzziness, people cannot recognize exactly the true behaviour of the predicted machine. When monitoring the parameters data, the measure behaviour and the choice of measure instruments or sensors bring subjective uncertainty inevitably. With improved methods, more accurate measure instruments or sensors and deeper investigations, subjective uncertainty can be reduced. Reducing the uncertainties to objective uncertainty is the final aim of uncertainty management research. Uncertainty management research also laid the basement for prognostics performance evaluation with the uncertainties.

3. Uncertainty sources analysis

The identification of uncertainty is the basis of the uncertainty management. According to the cognitive framework of prognostics uncertainty, the uncertainty sources are identified as three aspects:

"Machine": Machine refers in particular to the predicted systems. More Specific uncertainty sources can be derived from "machine", such as geometrical parameters and material physical properties of the machine. Such uncertainties of these uncertainty sources are objective uncertainty.

"Environment": Environment means load environment including working load and environment load. The predicted machine works in certain environment, which has great effects on the degradation of the machine and should not be ignored. The uncertainties of "Environment" are also objective uncertainty.

"Man": Man is the cognition subject of the machine-environment system. The results of treating to the predicted system contain subjective uncertainties and objective uncertainties. People take part in every step, from monitoring data to establishing the prognostics method of the prognostics system. Every step has several uncertainty sources such as data collecting uncertainty, data preprocessing uncertainty, failure criteria assessing uncertainty and prognostics methods establishing uncertainty.

✓ **Data collecting**: Monitoring data needs measure instruments or sensors. However, more than one measure instruments or sensors could be chosen, which will be affected by the cost or the presence of the measure instruments or sensors or individual preference. More choices will generate chosen random uncertainty. Besides, no measure instruments or sensors can monitor completely exact data that means measure errors being inevitable. The located position of sensors also affects the data accuracy.

✓ **Data preprocessing**: Experience has shown that even the simplest data collection systems can accumulate vast amounts of data quickly, requiring either a frequent download procedure or a large capacity storage device. In order to reduce the storage space, data-logger CPU loads and suitable for prognostics model, the data collected should be reduced. Data reduction methods conclude ordered overall range (OOR), rain flow cycle counting, range-pair counting, peak counting, level-crossing counting, fatigue meter counting, and range counting and so on. Due to more than one data reduction methods, the choice of the method has random uncertainty. Different data reduction methods have different processed results, which result in different prognostics results. Besides, the vast data collected contain noise and other disturbances inevitably. Noise reduction and data feature extraction should be carried out and the corresponding methods have more than one, which will bring in chosen random uncertainty.

✓ **Failure criteria assessing**: When the fault feature data grow to a predefined value, the predicted system is regarded failure. The predefined value is called threshold, which is assessed and defined beforehand. However, sometimes the failure threshold values of the predicted systems are not specific. They have random and fuzzy uncertainty. For example, in Miner's rule, the failure criteria values have a chosen interval [0.5, 2]. They have subjective uncertainty when predefining the threshold values.

✓ **Prognostics methods establishing**: Completely depicting the action of the fault state changing of the predicted system is difficult or impossible. Therefore, when setting up a prognostics method, approximate treatment principal is used. Different approximate treatment principals result in different structures of prognostics methods. Prognostics methods with different structures exist even to the same failure mechanism. The parameters of the prognostics methods also have uncertainty. For example, in Basquin's model, Steinberg (2000) using 6.4, while Mil-Std-810G (2008) using 4 as the fatigue constant.

The uncertainty sources stated above always fuse together. The fused uncertainties reflect on the input parameters, failure threshold and the prognostics method. For example, the parameters of the load environment incorporate the load data uncertainty, data monitoring uncertainty and data measuring uncertainty. Several low level uncertainties fusing can result in high level uncertainty. For example, the uncertainty of the fault feature parameters generates from the interaction of the uncertainty sources of the predicted system and the load environment uncertainty sources. High level uncertainty should be focus on when using the fault feature parameters to predict fault. When no high level uncertainty directly used, the subjective uncertainty should be focused on. Subjective uncertainty can be reduced and reducing such uncertainty is important in uncertainty management of prognostics.

4. General uncertainty management procedure

The most generally used term in the context of uncertainty is that of uncertainty management (Celaya, 2012). Uncertainty management is regarded to include uncertainty source identification, uncertainty qualification, uncertainty propagation and uncertainty feedback procession. The implementation procedure of uncertainty management is illustrated in Figure2.

Uncertainty sources identification is the first step of uncertainty management. The uncertainty qualification is following as the second step. Then the uncertainty qualified should be propagated from the input parameters and threshold to the prediction results. In uncertainty propagation, the uncertainty may be magnified. Therefore, the prediction results need to be evaluated and confirmed whether the uncertainty of the prediction results satisfy the user's requirement. If the requirement is satisfied, the prognostics results can be accepted. Otherwise, the feedback is needed. In the feedback, sensitivity analysis is carried out to rank the importance of the uncertainty sources. Then the important uncertainty sources will be processed more carefully, such as collecting more data or changing prognostics method, to reduce the predicted results uncertainty. Sensitivity analysis can be also carried out in the process of the uncertainty sources identification. By sensitivity analysis, the uncertainty sources that have tiny effects on prognostics results will be picked out and be processed as fixed values in prognostics, which can simplify the prognostics work.

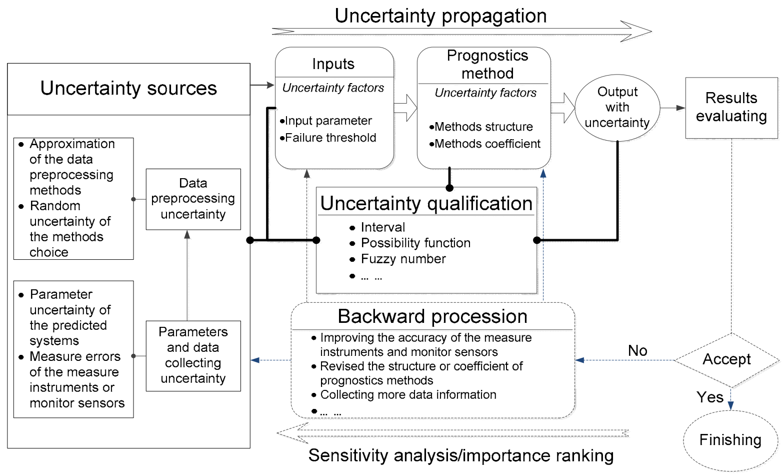

Figure 1: General uncertainty management procedure of prognostics system

(1) Uncertainty sources identification: Uncertainty sources have been identified systematically in part 3 according to the cognitive framework of prognostics uncertainty. In specific application, the uncertainty sources identified should be in accordance with the real application.
(2) Uncertainty qualification: Uncertainty qualification refers to representing the uncertainty in some mathematical formulas. Presently, the main areas of research in uncertainty qualification can be organized as probability-based methods, possibility-based methods and set–theoretical methods (Lopez, 2010).Figure 3 further depicts the strategy for uncertainty qualification.

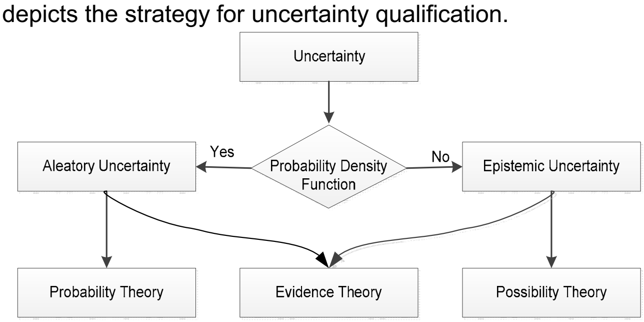

Figure 2: The strategy for uncertainty qualification

In uncertainty qualification methods, the probability theory is the most common method in prognostics (Oberkampf, 2004).When sufficient data information is available, probability distribution can accurately represent the random uncertainty. However, in real application, the information is always not sufficient, which results in lots of reducible uncertainty in prognostics uncertainty (Lopez, 2010, Zio, 2009).
(3) Uncertainty propagation: How to propagate the input uncertainty to the prognostics output results is a key point of uncertainty management. Presently, the uncertainty propagating methods include Monte Carlo method, improved Monte Carlo methods such as stochastic response surface method (SRSM), stochastic finite element method (SFEM), and interval-based method (Gareth, 2008).
Monte Carlo method is a common method used to propagate the uncertainty in prognostics because of its' wide adaptability. However, Monte Carlo method is a time-consuming method and the time consumed improves as the sampling times improve, which may lead to the timeliness of the prognostics dissatisfying users' requirement. The timeliness is an important metric of the prognostics performance. For the time-consuming shortcoming of Monte Carlo method, researcher developed several improved methods, in which SRSM and SFEM both can reduce the running time.
Interval-based method is applied when the uncertainties is qualified by interval numbers. Interval numbers have specific rules for the standard arithmetic operations of addition, subtraction. Therefore, the

uncertainties qualified with interval numbers can be easily propagated to the predicted results by the predicted models or related transfer functions. The predicted models or related transfer functions must be monotonic or the Interval numbers based calculation method does not work.

(4) Sensitivity analysis: Sensitivity analysis is the study of how the uncertainty in the output of a mathematical model or system (numerical or otherwise) can be apportioned to different sources of uncertainty in its inputs (Saltelli, 2008). Sensitivity analysis plays an important role in uncertainty management, which can be carried out in the design stage and feedback revised stage. In design stage, sensitivity analysis helps to find the important uncertainty sources of prognostics. Focusing on these important uncertainty sources will assist to improve the prognostics model. In feedback revised stage, if the uncertainty of the predicted results dissatisfy users' requirement, the important uncertainty gained by sensitivity analysis should be processed further in order to reduce the uncertainty of the results or consider changing the prognostics method.

Sensitivity analysis can be divided into local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis is simple but does not consider the interaction of the variables. Global sensitivity analysis considers the interaction of the variables. Therefore global sensitivity analysis is more truthfulness when the variables are not independent. Gu (2007) has analyzed the uncertainties of the prognostics of the printed circuit board working in random load environment, where the global sensitivity analysis and local sensitivity analysis were applied. The analysis result shows that the effect of the input uncertainty sources interacting together on the output uncertainty is smaller than the sum of the effects of the input uncertainty sources working separately.

Presently, sensitivity analysis method mainly includes Monte Carlo method, SRSM, Pearson's correlation coefficient method, the analytical moment based methods, the partial correlation coefficient methods and so on, where Pearson's correlation coefficient method, analytical moment based methods can be applied to analysis sensitivity globally and the partial correlation coefficient methods can be applied to analysis sensitivity locally. The applicability of the sensitivity analysis methods depends on the structure of the prognostics methods as well as the uncertainty propagation methods.

5. Uncertainty management for data-driven prognostics

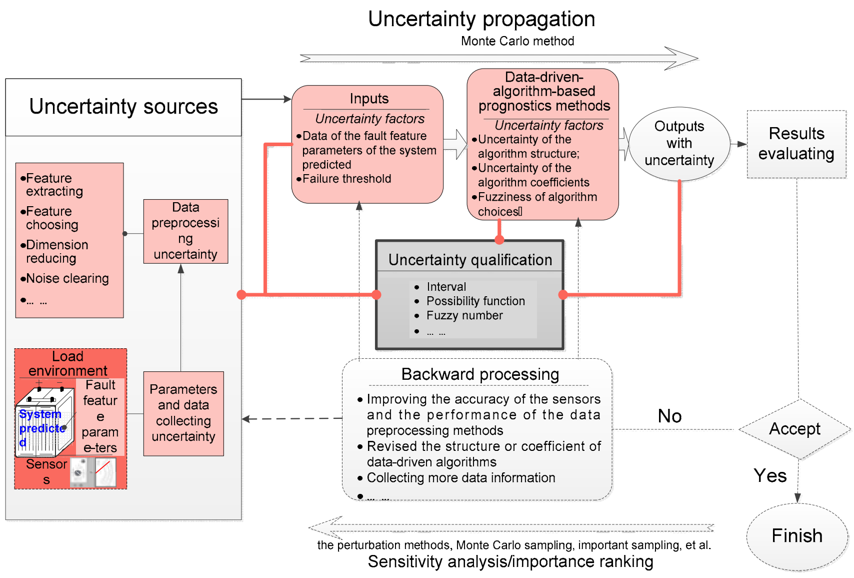

Figure 4: Uncertainty management procedure of the data-driven prognostics system

Data-driven prognostics approaches use real data (e.g. online gathered with sensors or operator measures) to approximate and track features revealing the degradation of components and to forecast the global behaviour of the predicted system (Kamal, 2009). Data-driven approaches do not have specific function expression. The input data are the fault feature parameters of the predicted system working in certain load environment. According to the general procedure of uncertainty management and considering the character of the data-driven approaches, the uncertainty management of the data-driven approaches based prognostics system is depicted in Figure 4.

Uncertainty qualification of the prognostics methods based on data-driven approaches mainly focuses on the uncertainty of the fault state feature data. The uncertainty propagation method for data-driven approaches is mainly Monte Carlo method because that the data-driven approaches don't have definite function expression. While the Monte Carlo sampling, important sampling, the perturbation methods et al. are always chosen for sensitivity analysis. When the specific data-driven method is chosen, more specifically sensitivity analysis methods can be used, seen ref (Cai, 2008) in detail.

6. Conclusion

A cognitive framework of prognostics uncertainty is presented from the perspective of *man-machine-environment* system engineering. Based on the cognitive framework, the uncertainty sources are systematically identified and analyzed from high level uncertainty sources to more specific uncertainty sources. Subjective uncertainties can be reduced, which is the focus of uncertainty management. The general process of uncertainty management for prognostics system is proposed. Uncertainty identification is the base of uncertainty management. The other parts of uncertainty management include uncertainty propagation and sensitivity analysis, which are all analyzed in detail. Based on the general process, the uncertainty management of typical data-driven method based prognostics system is analyzed. This study has guidance in implementing the uncertainty management of the prognostics system.

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