PhD Proposal 2017

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Title: Reliability prediction with hybrid model-based and data-driven methods
Scientific field: reliability prediction
Key words: reliability prediction, model-based, data-driven

Details for the subject:

Background, Context:

With growing awareness of reliability analysts which focus on detecting, predicting and ultimately preventing costly failures or long-term shutdowns, studies about Prognostics and Health Management (PHM) is attracting more and more attention from industry practitioners and academic researchers, especially in the structure-complicated and safety-critical systems such as energy plants, aircrafts, etc [1].

PHM is a method concerned with system “Reliability”. As the IEEE Standard 1413-1998 defines, “Reliability” refers to the ability that a concerning system maintain the desired performance under the desired condition and at the desired period. Generally, system reliability can be depicted as a quantitative index or be represented by some measurable system properties or their mixture. Through monitoring, estimating, and predicting the system reliability, the health state of a system can be evaluated, the advent of failure can be determined and the system risks can be mitigated. For this, an effective reliability prediction approach is firstly needed.

According to the difference of knowledge acquisition, the main reliability prediction methods can be classified into two categories: model-based methods and data-driven methods. The model-based methods look at the deterioration mechanism of a system to build a mathematical/analytical model to describe how system reliability evolves. Then, according to the monitoring data such as the system load, ambient temperature or other monitoring signals, the future system reliability is predicted. Commonly, these models are parametric and their prediction performances are tightly related to the parameters. With a detailed study about the evolution mechanism of system reliability and sufficient test experiments, the parameters setting can be fixed for improved performance. For example, through an impedance-based physic-chemical mechanism and extended accelerated tests, Ecker [2] proposed a parametric model to account for the impact of aging on the dynamic behaviour of lithium-ion battery:

$$\frac{L(T,V,t)}{L(T_0,V_0,t_0)} = 1 + B(T,V)\cdot c_a \cdot t^{1/2} \qquad ）1（$$

Based on this model, the lifetime of a high power lithium-ion battery under realist operation condition is successfully predicted.

The data-driven methods, contrarily, pay attentions to the historical data and the online monitoring data, and tend to regard the concerned system as a “black-box” with its property totally characterized by the collected data. Thus, many data analysis methods based from traditional statistical theory to intelligent machine learning theory are proposed to draw the system knowledge from data and build the extrapolation model to predict the future system reliability. In recent years, with the rapid development of computer and sensor technology, especially with the growing popularity of artificial intelligent approaches such as neural networks [3], genetic algorithm [4], particle swarm optimization [5] and support vector machine [6; 7], data-driven reliability prediction methods are attracting more and more interests. Now, the researches about data-driven reliability prediction methods are mostly focused on the structure of basic processes, uncertainty of algorithms, integration of different methods or models, and optimization of parameters.

However, the single model-based methods and data-driven methods both bear its own shortcomings that limit their further application.

The model-based methods rely heavily on the acquisition of accurate physical/mathematical models about the system. But in practice, as the concerned system is getting more and more large-scaled and complicated, the physical model representing the aging of the system or the evolution of its reliability becomes increasingly difficult to obtain.

Besides, a physical model is often constructed to a specific system; therefore, its generalisation ability is generally poor. So, the model-based reliability prediction methods are confronted with great challenges in the future.

The data-driven methods also suffer from some drawbacks. Since the data to support the method and the objective reliability evolution process are both stochastic, data-driven reliability prediction methods tend to be affected by uncertainty and be sensitive to divergence and local optimum. On the other hand, data-driven methods are highly-dependent on data sufficiency. Thus for systems without enough data, data-driven methods will show rather poor performance. Moreover, the computational complexity is always a significant restriction for data-driven methods.

Essentially, the model-based methods and data-driven methods represent different perspectives to understand the system. To take the advantages of both model-based and data-driven methods, and overcome their disadvantages, some fusion attempts to combine them seem to be reasonable. Thus, we propose a research plan aiming at fusion works of model-based and data-driven reliability prediction methods.

Research subject, work plan:

The study will focus on fusion works to combine the model-based and data-driven methods in reliability prediction problems. On the theoretical level, three progressive layers of “fusion” are expected:

1) Use one method to improve another. For model-based reliability prediction methods with difficulty to acquire an accurate physical model, some data-driven algorithms can be introduced to build a better model. And for data-driven methods with heavy computational complexity or that are vulnerable to divergence or local optimum, the model knowledge about system can be considered to accelerate the data-driven processes and improve the robustness..

2) Build multi-model fusion frameworks. More bricks of methods, including both model-based and data-driven, are considered to build multi-model frameworks. Then, some multi-model technologies, together with decision theory or fuzzy theory, etc, are introduced to manipulate the multi-model fusion system for a more comprehensive understanding about system reliability behaviour.

3) Propose new paradigms involving both model-based and data-driven methods. Rather than primitively integrating the model-based and data-driven methods as two separated parts, this layer of works tend to construct some original paradigms with the characteristics of both model-based and data-driven.

On the application level, the study will consider the following fields:

1) Large power plants, and key systems and components.

2) Complicated electric systems and key components.

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