Experiments for PHM: needs, developments and challenges

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ABSTRACT

The ultimate goal of Prognostics and Health Management (PHM) is to actively manage system health and accurately provide maintenance policy (Zio 2012). Remaining useful life (RUL) is an essential index for such purpose. When monitoring system performance data, varies of methods can be used for data fitting and the capability is highly depend on the generalization ability of the selected methods and the nature of data. However, for high-reliability and long-life products, it is difficult to get sufficient data to capture the degradation trend of the system even for a long time. Meanwhile, the correctness of the selection is hard to verify.

In order to select an applicable RUL prediction algorithm for such products, like battery, pump, etc. we consider the period before them putting into market, which is called the in-field development phase. Information about product design, tests, physical failure mechanism, etc. will be collected in this period. If those data can be used for building usage-oriented RUL prediction model, model selection will be a less problem for customers to understand the current health status of their products. Thus, we propose an experiment-based PHM framework to overcome the shortcomings.

Three time points at the in-field phase are considered: pre-design, final-design and trial. Firstly, simulation testing is given at pre-design stage using professional software, like AutoCAD, ANSYS, FLUENT. The purpose of this stage is to find the weakest link of the product design at component level and enhance system reliability by design modification. When accomplishing the correction loop, system degradation behavior can be simulated at the same time, based on which degradation modelling or algorithm selection can be undertook. We define the applicable model as M_1. Secondly, when it comes to final-design, accelerated testing is normally used to accelerate system degradation process since time is limited and precious for long-life products. Based on the failure/degradation data and accelerated model from simulation test, life prediction models can be updated from M_1 to M_2, which can be new models or partially from M_1, according to accelerated data. For instance, Weibull and exponential distributions are normally used for modelling failure time data, while degradation path-based, data-driven and stochastic processes for degradation behavior modelling. The relationship between stresses and degradation rate is handled by accelerated models like Arrhenius model (temperature), Eyring model (voltage) and others. Finally, trial test is conducted to examine system reliability under typical operation conditions. According to M_1 and M_2, the initial life prediction system will be set up and verified through trial test. Then, the collected information will upgrade the model from M_2 to M_3, which is much similar to the real operation model set M_4 that can be used for field RUL prediction by single prediction model with the highest prediction accuracy or the combined models from M_3. Overall, the tests at the in-field development phase contribute to the building of usage-oriented life prediction model set, achieving accurate life prediction results and right maintenance policy, which is significant different from that in traditional PHM methodology where the life prediction modelling mainly uses field monitoring data.

This paper presents the abovementioned experiment-based PHM methodology to improve the selection of life prediction model and data acquiring problems for high-reliability and long-life products in traditional PHM technique through the comprehensive use of in-field experimental information.

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ABSTRACT: Currently, the focus of reliability engineering has been extended from product design quality to product service, which drives the research on Prognostics and Health Management (PHM) methodology to provide timely and reliable service information about the health status of product. However, traditional PHM technique mainly concentrates on usage information which leads to the shortcomings of prediction modelling problems, especially for high-reliability and long-life products. This paper proposed an experiment-based PHM life cycle framework, aiming to integrate information from the in-field development phase to provide usage-oriented life prediction model set. When the on-line monitoring data is available, model set can be updated to acquire accurate prediction results and ensure effectively maintenance activity. In this paper, the life cycle is divided into seven stages and related modelling processes are given with specific case studies.

1 INTRODUCTION

Prognostics and Health Management (PHM) technique is to manage product health status through utilizing monitor information, do decision-making before failure happens and avoid catastrophe events, while reducing life cycle cost. The development of PHM represents that the focus of current reliability engineering has come into a new stage extended from quality-centered to service-centered, which can provide customers timely and reliable health information about their products and manage them properly. Among the service indexes, customers are mainly concerned about the Remaining Useful Life (RUL) which is to answer how much time is left for products to perform well. This demand promotes the deeper research on RUL prediction during the past decades, which is widely used in prognostics and maintenance scheduling for machinery, electronics and other products. The core of RUL research is to set up life prediction model whose accuracy will definitely affect the follow-up maintenance activity.

Traditional PHM extracts performance degradation pattern from real-time monitoring signal data or acquire degradation parameter data directly. Based on that information, life prediction model can be given according to the nature of data or the generalization capability of the selected models to capture the time-varying performance. However, it is difficult to verify whether the model itself is reasonable accuracy which will definitely increase the potential risk of product operation. Meanwhile, the advanced technology promotes the emergence of high-reliability and long-life products, which make it even harder to collect sufficient data for capturing the degradation process of such products in a limited time, especially for newly ones. Thus, traditional PHM technique faces the problem of life prediction modelling for the new generations which is high risky and less cost effective.

This paper at first reviews the existing research of traditional PHM in life prediction aspect and proposes an experiment-based PHM framework to overcome the abovementioned shortcomings. The usage-oriented life prediction model set is given at the in-field development phase and integrated with operational data to do health evaluation and maintenance decision-making. The rest of this paper is organized as follows. In Section 2, the research status of life prediction methods is analyzed and the existing problems are pointed out. The new framework is presented in Section 3 and three stages are mainly introduces, i.e. pre-design, after-design and field use, with related research contents for life prediction modelling. The flexibility of the framework is verified by case studies in Section 4. Section 5 concludes this paper.

2 REVIEW OF LIFE PREDICTION METHODS FOR PHM METHODOLOGY

RUL represents the length of time when product performance degrades below failure threshold or cannot meet the requirements, which is the key research of Condition Based Maintenance (CBM) and PHM (Jardine et al. 2006, Si et al. 2011). The RUL prediction methods can be divided into three categories: model-based (also called physical-based), data-driven and hybrid modelling (Heng et al. 2009, Zhou et al. 2013). Nevertheless, model-based methods require that the failure mechanism is known or degradation process can be analytical expressed, which cannot be applied for complex products, while data-driven methods is widely used since there is no need to know about the physical property. However, the prediction accuracy highly depends on the generalization capability of the selected models. The hybrid models integrate the strengths of both model-based and data-driven methods, which still cannot ensure the prediction accuracy.

The present research of RUL prediction in PHM technique mainly concentrates on product usage information. For the high-reliability and long-life products, the existing prediction methods have the following two problems:

– *Data:* How to collect sufficient monitoring data for the purpose of capturing the degradation process in a limited time?
– *Model:* How to establish reasonable life prediction models and simultaneously verify them for new products?

For the data problem, some research integrates expert knowledge or historical information with monitoring usage data. Zio & Di Maio (2010) proposed a similarity-based RUL prediction approach which utilizes the fuzzy similarity between system measurements with the reference failure trajectory patterns by giving related weights. Similar research refers to Wang (2011). Vaidya & Rausand (2011) studied the life extension problems of the equipment in offshore oil and gas industry which considers the influence of expert judgment, operational and environmental conditions, initial system state, etc. on RUL prediction. Chen & Tsui (2013) proposed a two-phase modelling method based on degradation signals which combines historical data with real-time monitor data to improve the RUL prediction results through Bayes theorem. Considering that in-field experiments, like Accelerated Testing, can shorten the test time effectively and gather performance degradation information rapidly for life prediction. Liao & Tian (2013) researched degradation modelling based on drift Brownian Motion and used Accelerated Degradation Testing (ADT) data to do model validation and parameters' evaluation, then the results are used as prior information for product RUL prediction under time-varying operational conditions. Similarly, Li et al. (2013) proposed an approach to build life prediction model based on degradation data under accelerated stress levels and the evaluated parameter results are used as prior information for RUL prediction in normal stress level. The case study shows that the proposed approach has a satisfactory prediction results even under the condition that field monitoring data is insufficient.

As for the model problem, researchers mainly do model comparison or combination to get the applicable prediction model. Saha et al. (2009a) compared several typical algorithms for battery RUL prediction, like Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), Relevance Vector Machine (RVM), etc. and results shows that integrated Bayesian regression and estimation methods, like SVM-PF, has significant prognostic advantage than traditional ARIMA and Extended Kalman Filter (EKF) methods. Then, Saha et al. (2009b) furthered this study. Caesarendra et al. (2010) studied the prognosis of complex devices based on sequential Mento Carlo method which shows a potential capability to predict trend data. Zio & Peloni (2011) proposed a RUL prediction method for non-linear component based on particle filtering (PF). Liu et al. (2012) proposed a data-model-fusion framework to improve the accuracy of long-term system state prediction results. Similarly, Zhao et al. (2013) offered a reliability prediction method which integrates PF and Support Vector Regression (SVR). Details about the hybrid prognosis algorithms in engineered system, readers are referred to Liao & Kottig (2014).

The above research papers partially answer the questions on both data and model for life prediction of high-reliability and long-life products. However, as described in Lee et al. (2014), explanation documents about the reason why select some specific prognosis algorithms still lack, which constrain the RUL prediction research into practical applications. Meanwhile, if we choose them blindly without reasonable basis, future life prediction activities will be extremely dangerous.

In order to solve those problems, we transfer the line of sight to the process before product put into market which is called the in-field development phase. In this phase, many experiments are conducted to ensure the requirement of high reliable and long life, among which reliability tests are the most important part. Through repeating the process of test-failure-fix, product life and reliability levels can be guaranteed to meet the design requirements (Collins et al. 2013). Meanwhile, this phase will accumulate a wealth of important information, such as failure mechanism, key components, accelerated testing data, etc. If those information can be properly utilized to build usage-oriented prediction model set, the life prediction problems for current PHM technique will be solved. Hence, an experiment-based PHM framework is proposed to make up the shortcomings for high-reliability and long-life products. The usage-oriented model set will also be verified at the in-field phase. When field monitoring data is available, the model will be updated and improved correspondingly to ensure the accuracy of life prediction results and maintenance activities.

3 THE EXPERIMENT-BASED PHM LIFE CYCLE FRAMEWORK

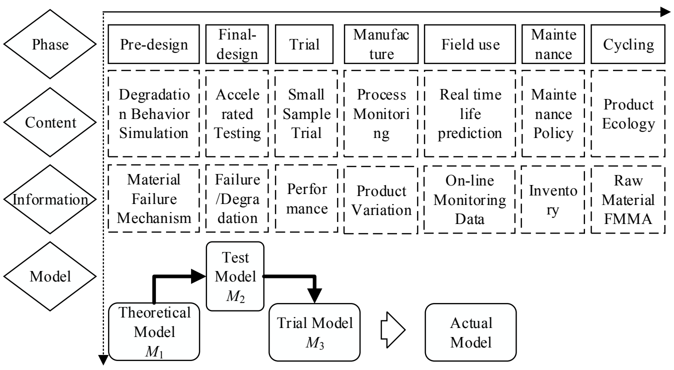

Figure 1. The experiment-based PHM life cycle framework.

For the purpose of solving existing life prediction problems in PHM, the experiment-based life cycle framework is proposed by integrating testing techniques at the in-field develop phase, including seven different stages which are pre-design, final-design, trial, manufacturing, field use, re-manufacturing and cycling, as shown in Figure 1. It should be mentioned that not all products experience these stages.

With the main line of life cycle stages, we introduce the interdependent relationship of the data and model under this framework, and provide their support for life prediction modelling.

In pre-design stage, which is also called concept demonstration phase, the feasible way is to carry out simulation test. According to the historical or similar product information and user requirements, we can acquire the material, geometric and other attributes. Then, product degradation behavior simulation can be undertaken based on Physics of Failure (PoF) model. This process covers from the determination of the degradation mechanism in component level to the degradation behavior modelling in system level, producing the weakest link of the design and assessing the life and reliability of products. Therefore, the design will be improved until the specific requirements are satisfied. Hence, this stage will set up the relationship among performance parameters, time and the stresses which is the theoretical life prediction model M_1.

$$M_1 : \begin{cases} P=f(t,M,S_{sim}) \\ T=g(P,S_{sim},D) \end{cases} \tag{1}$$

where M represents product material information; S_{sim} represents the specific operational conditions; D is the failure threshold. f represents the relationship among stresses, material and performance parameters, i.e. P, with time t, while g for stresses, performance parameters, threshold and product life T.

This relationship can be either analytical expression or data-driven models in accordance with the system complexity.

In final-design stage, in order to assess and verify the life and reliability level of product in a limited time, life prediction modelling based on accelerated testing will be carried out. With the input accelerated model M_1 from simulation test, ADT or ALT (Accelerated Life Testing) will be conducted to acquire accelerated data of product. When modelling the degradation data, both the models from M_1 and newly algorithms can be used and the most suitable model set, i.e. M_2, will be chosen for life prediction.

$$M_2 : \begin{bmatrix} M_{1\to 2} \\ M_{0\to 2} \end{bmatrix} \tag{2}$$

where $M_{1\to 2}$ represents the models inherited from M_1, while $M_{0\to 2}$ for the new ones.

Field trial can be arranged into different stages according to different purpose. For example, the trial is normally arranged into the middle of the development phase to reveal the early defect of product design, while after the final-design to assess if the reliability indexes satisfy the general requirements. No matter which stage that is, the field trial can appraise the actual performance level of product although that is not exactly the same one for future use. In this stage, initial PHM prediction module can be set up based on model set $[M_1, M_2]^T$, including sensor layout, data acquisition system and life prediction algorithms, etc. With the data from typical operational conditions, the most suitable prediction sets for field use are selected, M_3, which is the usage-oriented model set.

$$M_3 : \begin{bmatrix} M_1' & M_2' \end{bmatrix}^T = \begin{bmatrix} M_{11}', M_{12}', \cdots, M_{21}', M_{22}', \cdots \end{bmatrix}^T \tag{3}$$

where the symbol ' represents model updating.

In manufacturing, the consistency of production quality will be controlled by process monitoring, random sampling, etc. However, it is inevitable to introduce product variation which should be taken into consideration in future life prediction activity.

The above all stages is called the in-field development phase which utilizes the sub-stage data and models to provide usage-oriented prediction model set M_3. The contained models are verified through simulation, testing and trial. Therefore, the prediction results can be reasonable and accurate to avoid the prediction modelling problems in field actual use.

In field use, the monitoring data, like performance degradation, life and failure data, etc. is under actual operational and environmental conditions. Thus, the best prediction models or model combination, M_4, can be selected by ranking or assigning weights according to the prediction accuracy of M_3. Apparently, M_4 is a subset of M_3 but not a null set since the modelling process integrates all the information related to product.

$$M_4 : \{(M_4 \in M_3) \cap (M_4 \neq \varnothing)\} \quad (3)$$

At the end of field use, the product performance degrades nearly to the threshold and maintenance policy based on RUL should be carried out, like keep use after repair, replacement, etc. which can effectively prolong its life cycle and enhance system safety (You & Meng 2013). Just take battery as an example. The maintenance policy can provide battery manufacturing scheme, inventory and other information. If the battery completely scrap, it will be into the cycling stage to collect the raw materials and do Failure Mode and Mechanism Analysis (FMMA), which can be compared with the results of simulation test to adjust model set M_1. This improvement will be feedback to the battery design of next generation, thus to achieve the ecological life cycle management.

Overall, the proposed experiment-based PHM framework can utilize all the information from the in-field development phase to provide usage-oriented life prediction set and verify it simultaneously, specifically the life and reliability tests before products are put into use. This overcomes the shortcomings of traditional PHM technique on model selection and data acquisition in the aspect of life prediction. The framework is applicable to the new products which have high-reliability and long-life properties, providing technical support for the new reliability engineering area which centers in intelligent service. Therefore, it has practical engineering value and broad development prospects for the implement of PHM system in engineering applications.

The specific modelling process for several typical stages are given below:

3.1 *Product degradation behavior simulation based on PoF models*

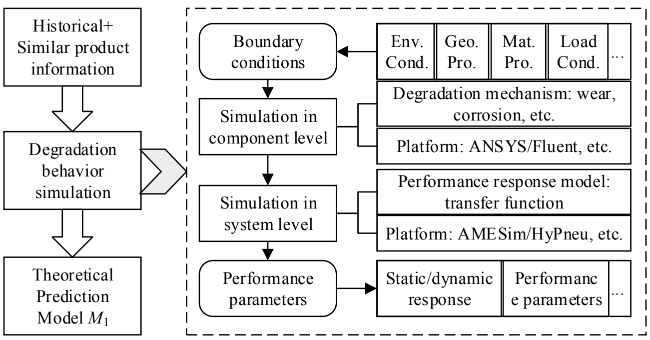

Figure 2. Degradation behavior simulation based on PoF models.

The goal of product degradation behavior simulation is to acquire performance data varying with time under specific conditions and find out the weakest link of product design.

This process uses historical and similar product information, and expert knowledge as inputs. The output is the theoretical life prediction model set M_1 (Fig. 2).

Conventional layer classification is the first step for product analysis. Then, the related failure mode and mechanism, environmental and load conditions, and other information should be determined to conduct performance simulation in component level. Through the transfer function between system and component levels, performance simulation in system level can be carried out, collecting simulated performance data varying with time under specific conditions. Finally, modelling the degradation process with consideration of the failure threshold is to produce the model set M_1. Noting that theoretically physical model can be established for product with simple failure mechanism, while modern engineering tools should be used for complicated products. Thus, the model set M_1 can be analytical functions or data-driven models.

The selected models are applicable to describe the properties of product performance which, however, are under many assumptions, like boundary conditions, etc. which may not be suitable for real applications. Therefore, more test data is needed to verify the feasibility of M_1.

3.2 *Life prediction modelling based on accelerated testing*

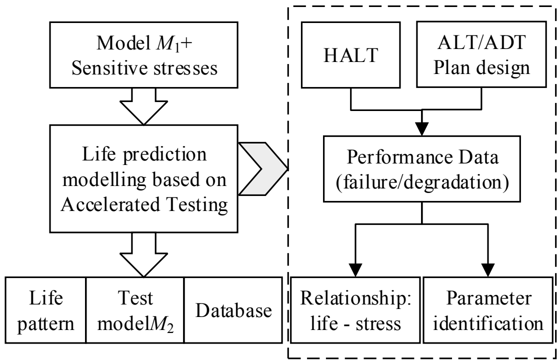

Figure 3. Life prediction modelling based on accelerated tests.

For high-reliability and long-life products, accelerated tests are normally used to evaluate its life and reliability by experiencing severe stress levels than that in normal conditions to accelerate product failure or degradation process. Thus, sufficient data will be obtained in a short period of time and used for life prediction modelling. This process is dependent on the basis of accelerated model from simulation test, i.e. M_1, and the sensitive stress to conduct accelerated test. Then, suitable models will be selected from M_2 based on the test data, see Figure 3.

This stage is usually first carry out the qualitative accelerated tests, such as High Accelerated Life Test (HALT), etc. to obtain the stress limit where product can still function well. Then, with the input from simulation test, quantitative accelerated tests will be carried out, such as ALT, ADT, etc. including test plan design (Tseng et al. 2009, Liu & Tang 2010) and data proceeding (Meeker et al. 1998, Escobar & Meeker 2006). For the proceeding of accelerated test data, the models from M_1 should be verified and eliminated the unreasonable ones, while new models can be introduced. Therefore, the new level prediction model set is achieved, i.e. M_2.

Being similar to the selected procedure in simulation stage, the models in this stage still need further screening process since there are still exist many assumptions, like stress simplification, ignoring multi-degradation mechanism, etc.

3.3 *On-line predictive maintenance through PHM*

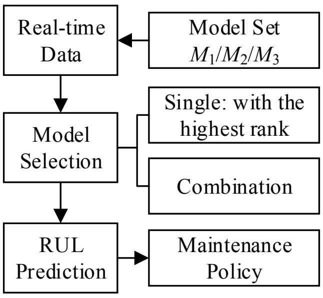

Figure 4. On-line Life predictive maintenance through PHM.

Traditional PHM technique mainly focus on field use information by which to evaluate product health status and offer maintenance policy, i.e. CBM (Niu et al. 2010, Meng & You 2011). However, this technique has its limitations when applying to high-reliability and long-life products. On the contrary, the experiment-based PHM framework provides alternative prediction model sets M_1, M_2 and (or) M_3 at the in-field development phase, which can be used for field life prediction. Figure 4 illustrates this process.

When field monitoring data is available, life prediction can be accomplished by either single model with the highest rank or combined models with their weights according to the prediction accuracy. Its procedure is significant different from the traditional selection method without criteria and it can achieve reasonable RUL prediction results and ensure the effectiveness of maintenance decision-making.

4 CASE STUDIES

The below several cases are used for describing the field RUL prediction modelling based on the information from each life cycle stage under the experiment-based framework. It should be noted that partially tests are carried out for the specific applications at some stages, but all the information collected from this tests do help modelling the RUL prediction for field use.

4.1 *Life prediction modelling for Double nozzle flapper electro-hydraulic servo valve*

Electro-hydraulic servo valve is a key control unit widely used in modern aircraft. In practical application, servo valve is susceptible to the effect of the oil particle pollution which affects its performance, causing the wear of the valve core and sleeve edge. The influence mainly includes pressure gain, inner leakage, etc.

For the purpose of evaluating the life and reliability indexes of servo valve, both simulation test and accelerated test are conducted before that is put into use. The information obtained from the two tests are used for life prediction modelling according to the procedure in Section 3.1 and 3.2. The results are shown in Figure 5. At first, the wear of nozzle flapper and sliding valve under the influence of oil pollution is simulated through FLUENT software in component level, acquiring the wear degradation process of structure parameters varying with time (Fig. 5a, 5b). Then, the data is used as input for system level simulation through transfer function which shows the link between components and system (Fig. 5c) using AMEsim software. Finally, the degradation behavior of system performance is obtained which shows that the pressure gain reduces with time, while leakage flow increases. After the simulation test, the collected data is also used for designing accelerated plan. The optimal plan is Step Stress ADT (SSADT) with 5 stress levels (oil pollution degree) and 3 samples. The monitor interval is 2 hours and the performance parameters are pressure gain and leakage flow, see Figure 5d. After the test, the edges of valve core wear severely.

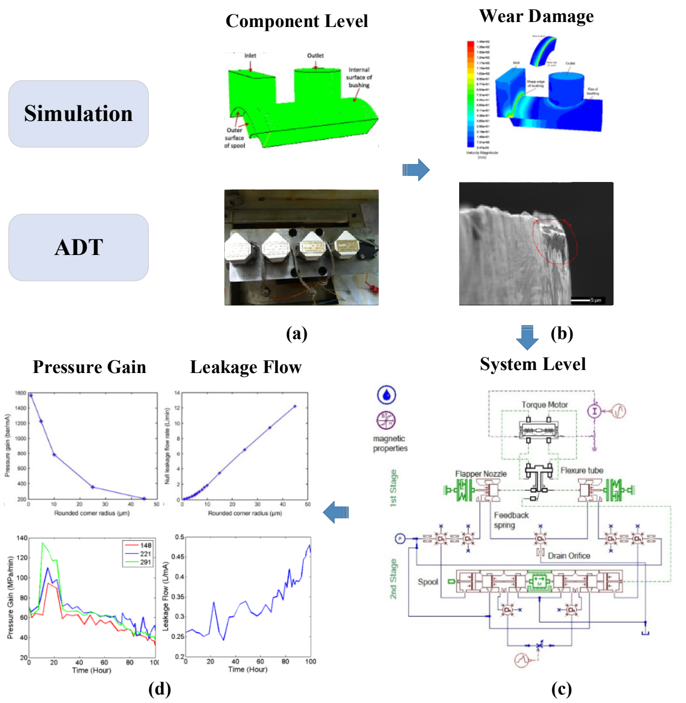

Figure 5. Life prediction modelling for Double nozzle flapper electro-hydraulic servo valve.

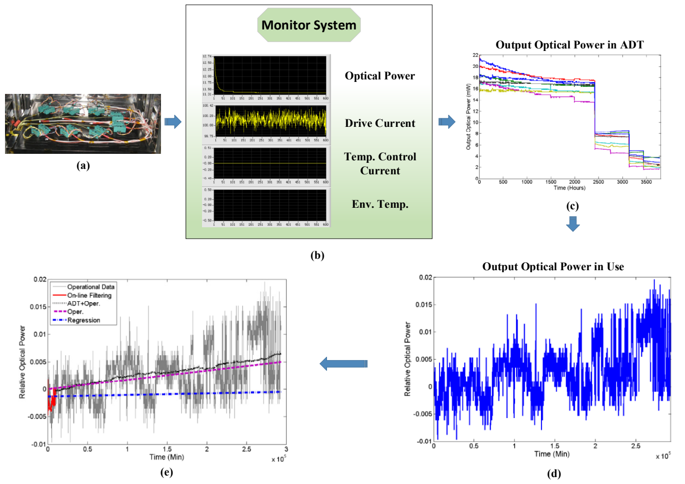

Figure 6. Life prediction modelling based on ADT data and on-line updating through Bayesian approach for super luminescent diode.

Based on the degradation data from simulation and accelerated tests, the life prediction models M_1 (Quadratic or linear function) and M_2 (drift Brownian Motion) can be given by integrating with the failure thresholds (25% initial pressure gain and 10% rated flow-rate). Details are referred to Zhang et al. (2014) and Wang et al. (2014). The model set then will be used for field life prediction. This modelling procedure is also applicable to other products by building usage-oriented prediction models and being verified for field use, which can definitely guarantee the accuracy of prediction results.

4.2 *Life prediction modelling and on-line updating for super luminescent diode*

Super Luminescent Diode (SLD) is a kind of one-way light amplification devices which has excellent properties, like wide spectrum, high power. Light SLD is one of the key functional modules of fiber optic gyroscope, experiencing temperature stress in practical use. The inner components degrade with time and that decrease the output optical power.

SLD belongs to high-reliability and long-life product which should be in use for several years. If the life prediction modelling only rely on field use data, sufficient data is needed to capture the degradation process which, however, is hard to acquire even for a long time. Thus, the models based on this data cannot ensure the prediction results. Before SLD is put into market, ADT was carried out at the in-field phase. According the procedure from Section 3.2, eight samples and four temperature stress levels were used in the SSADT (Fig. 6a, 6b). The monitoring parameter is the output optical power which is shown in Figure 6c. Therefore, the life prediction model M_2 (drift Brownian Motion, etc.) can be built based on the ADT data. When on-line data is available (Fig. 6d), the model is updating with time through Bayesian approach. The prediction results show that this method has higher accuracy than the traditional regression method which only uses the field data. Meanwhile, monitoring data in a limited time is enough for modelling the degradation process for this kind of product (Li et al. 2013).

4.3 *Life prediction based on combined algorithms*

This case is to describe how to use the usage-oriented model sets to conduct field RUL prediction. Commonly used method is single prediction model or combined models with associated weights according to their prediction accuracy. Here, we only consider the combined model for life prediction.

As shown in Section 3.3, the input is the model sets, M_1, M_2 and (or) M_3 which are BP neural network (f_1), drift Brownian Motion (f_2), time series model (f_3) and particle filtering model (f_4). Degradation data for the particular optical device was collected in field use for 480 hours (Fig. 7a). The first half is used for model training, while the rest for validation. Then, training data is fitted by each single model and encompassment test is conducted to do model selection. The ranking result based on their prediction accuracy is $f_3>f_2>f_1>f_4$ and the encompassment test rejects model f1. Thus, the other three models are combined for RUL prediction in the following process. Combinatorial optimization algorithm, like the particle swarm optimization with immunity algorithms (IA-PSO), is used to assign weights for the three models (Fig. 7b) which are 0.288, 0.712 and 0, respectively. Finally, we use the rest data to verify the prediction accuracy and the result is $f_{com}>f_3>f_2$. Hence, the combined model perform better than the single forecasting models (Fig. 7c). Details are referred to Feng et al. (2014).

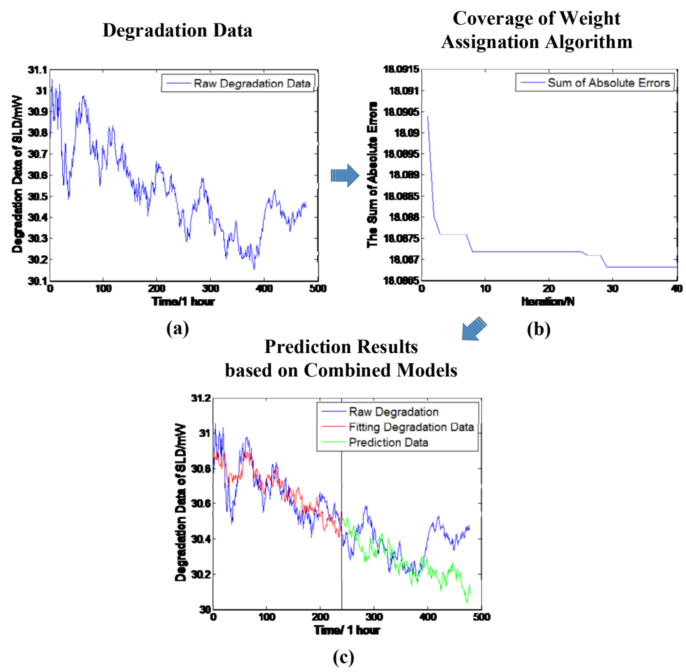

Figure 7. Life prediction based on combined algorithms.

The experiment-based PHM framework can provide usage-oriented prediction model at the in-field development phase for field RUL prediction, which is superior to the traditional methods that mainly rely on field monitoring data.

5 CONCLUSIONS

Nowadays, the PHM technique has been applied in rotating machinery, batteries and other complicated equipment, providing on-line health evaluation results of the product to users and saving maintenance cost (Sikorska et al. 2011, Zhang et al. 2011, Lee et al. 2014). However, traditional PHM technique mainly focus on the monitoring data from field use to undertake RUL prediction modelling, which has shortcomings on both data and model for high-reliability and long-life products. Therefore, this paper proposed the experiment-based framework to integrate all the information from in-field phase to do life prediction modelling from the perspective of total life cycle. The prediction model sets keep updating with the information accumulating to ensure the effeteness of prediction activity. At the viewpoint of reliability engineering, this is also a new development of reliability growth program. The usage-oriented life prediction model set is given and verified at the in-field development phase, which definitely ensure the accuracy of prediction results.

The values of the experiment-based PHM technique are on:

– Integrating the idea of prognosis and acceleration to enrich the connotation of reliability engineering.
– Supporting the total life cycle management of product with the further development of reliability platform, which can be widely used in aerospace, automotive, energy and other fields.
– Shortening the product development time by improving product reliability and life expectancy, realizing intelligent maintenance to ensure its safety and economy, achieving green product ecology.

The development of high-reliability and long-life products promotes new requirements for current reliability engineering systems. The proposed experiment-based framework integrates diagnostics, prognosis and health management with reliability testing methods, providing a feasible idea to achieve total life cycle management.

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