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A Framework for Remaining Useful Life Prediction of Steam Turbines Applicable to Various Data Types

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Abstract

A Framework for Remaining Useful Life Prediction of Steam Turbines Applicable to Various Data Types

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The power plant industry focuses significant effort on reducing operation costs and extending the service life of critical machines as competition between utilities increases. On the other hand, the deterioration of core facilities (e.g., steam turbines) of the power plant is accelerated as operating time closes to design life. Unplanned outages of power plant due to accelerated degradation or unexpected failure, whether sustained or only momentary, can lead to considerable financial losses as well as nationwide disaster. Thus, various methodologies are being developed to enable stable operation of the power plant without failure. Recently, prognostic and health management (PHM) has been successful in various industries by predicting the health condition of the system and helping managers make decision for optimal maintenance.

From the perspective of optimal maintenance, the remaining useful life (RUL) obtained by suitable PHM methodologies make it possible to perform effective maintenance management based on the actual condition of the facilities. Since a steam turbine is a key facility to determine a design life of power plant, an effective method is required to predict accurate RUL for steam turbine in service through the limited and available resources. In order to facilitate the development of formal methodologies for this needs, this doctoral dissertation aims at advancing three essential and co-related research areas for RUL prediction of steam turbine using Bayesian approach: (1) Research Thrust 1 – an RUL prediction framework for steam turbine with failure mode and effective analysis (FMEA) analysis; (2) Research Thrust 2 - a damage growth model for RUL prediction of steam turbine (empirical model-based approach); and (3) Research Thrust 3 - a mode-dependent damage model for steam turbine with creep-fatigue interaction (physical model-based approach). The research scope in this doctoral dissertation is to develop technical advances in the following three research thrusts:

First, Research Thrust 1 proposes an RUL prediction framework for steam turbine with FMEA. The framework is composed of two approaches: measured data-driven and damage model-based methodologies. The proposed RUL prediction framework with uncertainty quantification step enables the statistical prediction of RULs. The key to success in this effort is to quantify and reduce uncertainties of predicted RUL results considering different purpose such as off-line and/or on-line prediction.

Second, Research Thrust 2 aims at developing damage growth model for RUL prediction of steam turbine based as data-driven approach. An RUL prediction methodology incorporates a damage index into the damage growth model. A Bayesian inference technique is used to consider uncertainties while estimating the probability distribution of a damage index from on-site hardness measurements. The predictive distribution of the damage index is estimated using its mean and standard deviation. As a case study, real steam turbines from power plants are examined to demonstrate the effectiveness of the proposed Bayesian approach. The results from the proposed damage growth model can be used to predict the RULs, including uncertainties, of the steam turbines of power plants regardless of load types (peak-load or base-load) of the power plant.

Finally, Research Thrust 3 proposes a mode-dependent damage model with creep-fatigue interaction as a model-based approach. The effect of operation and damage mode on the creep and fatigue damage was statistically investigated in terms of creep-fatigue damage interaction effects. The three steps are systematically organized as follows: (1) statistical calculation of dominant damage mechanisms; (2) development of mode-dependent damage model with creep-fatigue interaction effects; (3) investigation of interaction effects according to the operation and damage modes.

Keywords: Steam turbine
Remaining Useful Life (RUL)
Uncertainty
Bayesian inference
Creep-Fatigue Damage Interaction

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Nomenclatures

N	number of cycle at a given strain range
N_f	the pure fatigue life at a given strain range
t	operating time
t_r	rupture time
e, r	interaction parameters
N_{ij}	number of cycle between a plastic-creep loops
A_{ij}	cycle parameter between a plastic-creep loops
$\Delta\varepsilon_{ij}^{ojk}$	strain range between a plastic and creep loops
S	strain range
R	strain rate
T	Temperature
H	hold time parameter
$D(t)$	time dependent damage function
$N(\mu,\sigma)$	normal distribution
$\mu_D(t)$	time-dependent mean function
$\sigma_{\mathrm{D}}(t)$	time-dependent standard deviation function
EOH	equivalent operating hour
t_{op}	operating hour
LF	the life factor
N_{op}	the number of starts
D	damage index
$\widetilde{H}$	hardness in damaged material states
H	hardness in undamaged material states

H_a	hardness measured at aged material states
H_v	hardness measured at virgin material states
$\tilde{E}$	elastic modulus in damaged material states
E	elastic modulus in undamaged material states
$\tilde{\rho}$	density in damaged material states
ρ	density in undamaged material states
$\tilde{v}$	ultrasonic wave in damaged material states
v	ultrasonic wave in undamaged material states
$\Delta\sigma^*$	cyclic stress amplitude in damaged material states
$\Delta\sigma$	cyclic stress amplitude in undamaged material states
$\dot{\varepsilon}_p^*$	minimum creep rate in damaged material states
$\dot{\varepsilon}_p$	minimum creep rate in undamaged material states
j	material parameters of tertiary creep
$\tilde{V}$	potential difference in damaged material states
V	potential difference in undamaged material states
∂S_D	area of the plane
∂S	effective area of the plane
α_μ, β_μ	hyper-parameters for mean of damage indices
$\alpha_\sigma, \beta_\sigma$	hyper-parameters for standard deviation of damage indices
U_m	area metric
F_u	transformation of every damage index into the CDF of responses from an assumed model
F_{uni}	CDF of a uniform distribution *U(0,1)*
z	conditional on the given parameters θ
$p(\theta \vert z)$	posterior distribution of θ conditional on z
$L(z \vert \theta)$	likelihood of the observed data
$p(\theta)$	prior distribution of θ

α, β	hyper-parameters for the mean and standard deviation of the damage indices
$p(\alpha_\mu, \beta_\mu \vert \mu)$	posterior distributions of the hyper-parameters for the mean of the damage indices
$p(\mu \vert \alpha_\mu, \beta_\mu)$	likelihoods of the hyper-parameters for the mean of the damage indices
$p(\alpha_\mu, \beta_\mu)$	prior distribution of the hyper-parameters for the mean of the damage indices
$p(\alpha_\sigma, \beta_\sigma \vert \sigma)$	posterior distributions of the hyper-parameters for the standard deviation of the damage indices
$p(\sigma \vert \alpha_\sigma, \beta_\sigma)$	likelihoods of the hyper-parameters for the standard deviation of the damage indices
$p(\alpha_\sigma, \beta_\sigma)$	prior distribution of the hyper-parameters for the standard deviation of the damage indices
s_μ, s_σ	variances of the mean and standard deviation of the damage indices
$\alpha^L, \alpha^U, \beta^L, \beta^U$	lower and upper bounds of the hyper-parameters of the mean and standard deviation
D_c	value of the critical damage
P	Larson-Miller parameter
C	material constant of the Larson-Miller Parameter
A_1, A_2, A_3, A_4	regression parameters of the Larson-Miller Parameter
σ	Stress
D_{creep}	creep damage rate
ε	total strain
ε_e	elastic strain
ε_p	plastic strain
C_1, C_2, α, β	material constants of the Coffin-Manson relation
$D_{fatigue}$	fatigue damage rate
F	functional form of the log-normal and weibull distributions

φ	scale parameter of the weibull distribution
τ	shape parameter of the weibull distribution
σ_r	radial stress
σ_t	circumferential stress
ν	Poisson's ratio
W	weight
ω	rotation speed
g	gravity acceleration
r_i	inner radius
r_o	outer radius
σ_{bore}	stress at bore
$\sigma_{surface}$	stress at surface
a	inner radius of turbine rotor
b	outer radius of turbine rotor
$C_{\max}$	dimensionless nominal thermal stress
$\sigma_{\max}$	maximum stress
ΔT	maximum temperature difference
K_T	thermal stress concentration factor
K_ε	plastic strain concentration factor
d	diameter of turbine rotor
R	curvature at 1st stage of turbine rotor
DEQ	vector of the input random variables
d_d	diameter of turbine rotor disk
d_s	diameter of turbine rotor
L	width of blade disk
ϑ	normalized nominal strain range

$\Delta\varepsilon_t$	total strain range
ε_y	cyclic yield strain

Chapter 1

Introduction

1.1 Motivation

The deterioration of core facilities, large industrial facilities such as power plant, is accelerated as operating time goes by. Unplanned shutdown due to degradation or unexpected failure, whether sustained or only momentary, can lead to considerable financial losses as well as nationwide accidents. The 2011 South Korea Blackout, which had an economic loss of about 63 million dollar, was a power outage across South Korea on September 15, 2011. It was known that this is caused by an unexpected failure of the old components, not a mistake of forecasting electric power demand. As shown in Figure 1-1, more than one-third of facilities are operating for more than 20 years among domestic power generation facilities. Therefore, it is necessary to maintain stable operation in consideration of accelerated aging of old facilities in order to prevent unexpected power outages. Recently, prognostic and health management (PHM) has been successful in various industries by enabling proactive maintenance decisions beyond conventional preventive maintenance. PHM technologies can effectively predict the health condition of the system and help managers make decisions for optimal maintenance.

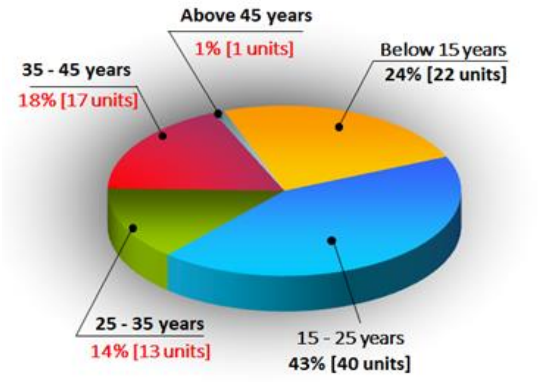


Figure 1-1 Status of coal fired and NG power plant in Korea (2010)

From the perspective of optimal maintenance, the remaining useful life (RUL) obtained from the accurate prediction make it possible to perform maintenance management based on the real state of the facilities, rather than conservative maintenance strategy; time-based replacement or new construction following recommendation of the manufacturer. In case of power plants, the new construction cost (1000~1500$/kW) is larger than life extension cost (150~200$/kW) as shown in Figure 1-2. Thus, new PHM technologies that tracking changes in the health condition of power plants and predicting its RUL is becoming a constant topic of power generation industry. Accurate RUL prediction by PHM technologies should be developed to extend conservative service life, and to secure reliability and stability of plant.

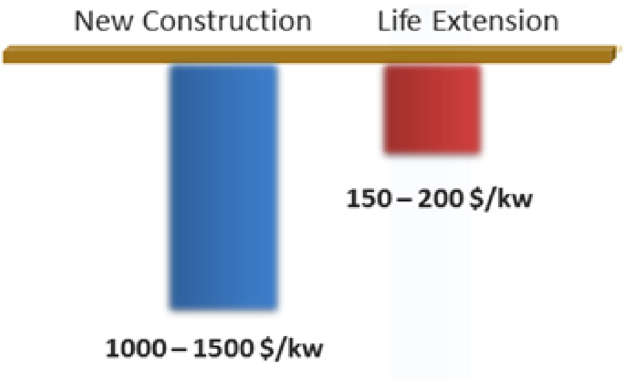


Figure 1-2 Comparison of new construction and life extension cost for power plant

Especially, it is important to predict the RUL of the turbine in assessing the state of the plant since steam turbine is a key facility that determines service life of power plant. It is well known that expected service life of turbine is about 20-25 years according to the guideline of manufacturing companies.

Many research efforts have been made to develop RUL prediction methodologies for major component of power plant. However, there is still a great need for RUL prediction methodologies using actual operation conditions for important component such as turbine, not limited to test material in laboratory. The advantages and disadvantages are clearly distinguished from the data-and model-based methodologies. Thus, it is necessary to develop novel methodologies to eliminate uncertainty and to improve the accuracy of RUL prediction in a given condition.

First, RUL assessment guidelines are depend on individual method such as replication, hardness, analytic method and so on, respectively. And there is no valid framework to predict RUL of turbine considering various purposes including online or offline estimation. If it is possible to obtain sensory data from a real steam turbine, second, obtained data can be analysed and used to predict RUL using statistical approach such as Bayesian inference. Finally, there is a need for a methodology to predict the RUL when there is an appropriate physical model though it is difficult to obtain data on site.

As a result, the above three technical challenges should be properly addressed to successfully predict RUL of steam turbine.

1.2 Research Scope and Overview

This doctoral dissertation aims at advancing three essential and co-related research areas for RUL prediction of steam turbine: (1) Research Thrust 1 – an RUL prediction framework for steam turbine applicable to various data types after FMEA analysis; (2) Research Thrust 2 - a damage growth model for RUL prediction of steam turbine (empirical model-based approach); and (3) Research Thrust 3 - a mode-dependent damage model for steam turbine with creep-fatigue interaction (physical model-based approach). The research scope in this doctoral dissertation is to develop technical advances in the following three research thrusts:

Research Thrust 1: An RUL Prediction Framework for Steam Turbine with FMEA Analysis

Research Thrust 1 proposes an RUL prediction framework for steam turbine with failure mode and effective analysis (FMEA). Many research efforts have been devoted to the RUL prediction of high temperature components. To the best of the author's knowledge, previous researches have not been able to systematically organize step-by-step procedure, but those are tendency to bias how the calculations are carried out accurately in each step. This thrust places the main focus on the design of RUL prediction framework based on FMEA results. The framework is composed of two approaches: measured data driven and damage model based methods. The proposed RUL prediction framework with an uncertainty quantification enables the statistical prediction of RULs.

Research Thrust 2: A Damage Growth Model for RUL Prediction of Steam Turbine (Empirical model-based Approach)

Research Thrust 2 aims at developing damage growth model for RUL prediction of steam turbine based as data-driven approach. The hardness measurement is most commonly and easily used in actual field for RUL prediction. However this method is subject to uncertainties due to aleatory and epistemic uncertainties in irregular and discontinuous measurement and non-homogeneous samples. A Bayesian inference and MCMC sampling technique are used to consider uncertainties while estimating the probability distribution of a damage index from on-site hardness measurements. The predictive distribution of the damage the damage index and RUL are estimated for retired turbines to determine a threshold which is of great importance to RUL prediction. As a case study, real steam turbines from power plants are examined to demonstrate the effectiveness of the proposed Bayesian approach. The results from the proposed damage growth model can be used to predict the RULs of the steam turbines of power plants regardless of load types (peak-load or base-load) of the power plant.

Research Thrust 3: A Mode-Dependent Damage Model for Steam Turbine with Creep-Fatigue Interaction (Physical Model-based Approach)

Following the development of Research Thrust 1 and 2, Research Thrust 3 proposes a mode-dependent damage model with creep-fatigue interaction as a model-based approach. The accurate knowledge of damage rate or risk of the steam turbine is critical to the necessary for the effective operation and maintenance of power plant. Many researches are carried out to investigate the creep and fatigue damage behavior of steam turbines that operated under high temperature and frequent loading condition. However, there is a growing reliability concerns as the operation mode has shifted in the direction of accelerating significant damages to the steam turbine. This study proposes a damage interaction model based on combining creep and fatigue damage with actual field data and material test data. The interaction effects of operation and damage modes on the creep and fatigue damages are statistically investigated in terms of creep-fatigue damage interaction effects. Additionally, risk is evaluated using the proposed mode-dependent damage interaction model.

1.3 Dissertation Layout

This doctoral dissertation is organized as follows. Chapter 1 reviews the current state of knowledge regarding life prediction. Chapter 2 proposes a practical RUL prediction framework of steam turbine with FMEA (Research Thrust 1). Chapter 3 presents a damage growth model using sporadically measured and heterogeneous onsite data (Research Thrust 2). Chapter 4 discusses mode-dependent damage assessment with creep and fatigue interaction model. Finally, Chapter 5 summarizes the doctoral dissertation with its contributions and suggests future research directions.

Chapter 2

Literature Review

To provide readers with sufficient background information, this chapter is designated to present the literature reviews of the knowledge within the scope of this doctoral dissertation: (1) life prediction methodologies of steam turbine; (2) measured data driven life prediction; (3) damage model based life prediction using creep and fatigue damage analysis. Literatures on each of these three aspects are discussed in one subsection and challenges are addressed. Since this doctoral dissertation focuses on how to estimate remaining useful life and evaluated total damage rate by means of real field data from steam turbine, general characteristics of prognostics and health management of engineering systems are not reviewed in detail here and such works can be found in the existing review articles.

2.1 Life Prediction Methodologies for Steam Turbine

The design life of steam turbines is typically 25 years or 200,000~250,000 hours [1-3]. The power plant industry focuses significant effort on reducing operation costs and extending the service life of critical machines (e.g., steam turbines) to avoid premature failure. Condition-based maintenance (CBM) has drawn great attention as a strategy for cost-effective operation and maintenance (O&M) decisions. A CBM program consists of four main steps: data acquisition, data processing, health prognostics, and maintenance decision-making [4, 5]. The health prognostics step includes not only diagnostics for fault detection, isolation, and identification; it also includes prognostics for predicting the remaining useful life (RUL) before failure [6-8]. There are increasing demands for engineering aftermarket services to manage steam turbines in a timely and proper manner [9]. RUL prediction for complicated and large-scale systems is a major scientific challenge and a significant issue for effective O&M. With respect to turbines that are already in service, an effective method is required to accurately predict RUL through the limited available resources [10].

Major components of power plants are exposed to harsh thermal loading conditions. Theoretically, the RUL of key components could be predicted by metallurgical or theoretical analysis of as-received and degraded elements [1]. Recent life assessment technology and applied experience for existing steam turbines are described in Table 2-1. In general, it is well known that there are mainly three kinds of life assessment methods for steam turbine; the destructive, the nondestructive and the analytical method [11].

Table 2-1 Comparison of RUL Prediction (life assessment) methods for Steam Turbine

Approach		Destructive	Non-destructive	Statistical	Analytic
Feature		· Direct · Inconvenient/limited · Partially predict RUL life	· In-direct · Convenient/limited · Not predict RUL life	· In-direct · Mathematical function · Failure data dependent · Predict RUL life	· Complex calculation · Physical model · Predict RUL life
Prediction area	Stress Concentration area	· Partially applicable	· Partially applicable	· Partially applicable	· Applicable
	Flat area	· Applicable	· Applicable	· Partially applicable	· Applicable
RUL prediction	Creep	○	○	△	△
	Fatigue	○	X	△	△
	Creep-fatigue interaction	○	X	△	△
Assessable damage range	Creep	Full damage range	· Partially applicable	· Partially applicable	· Full damage range
	Fatigue	· Not applicable	· Not applicable	· Partially applicable	· Full damage range
	Creep-fatigue interaction	· Not applicable	· Not applicable	· Partially applicable	· Full damage range · Damage interaction Model required
Method		· Tensile test · Creep rupture test · Fatigue test · Cavitation analysis	· Replication · Hardness measurement · Indentation test	· Regression · Neural Network · Bayesian (with model)	· Finite element analysis · Probabilistic analysis

2.1.1 Destructive Method

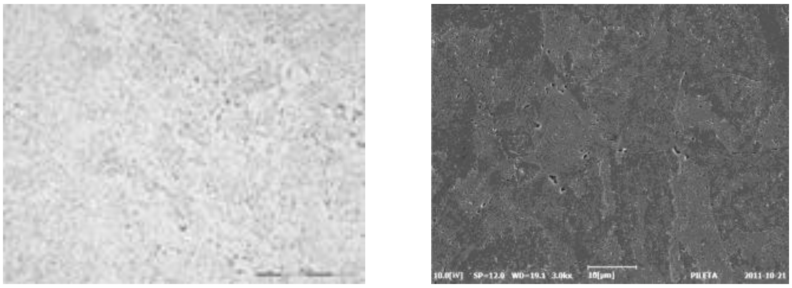
Although the destructive method can directly evaluate the metallurgical property in laboratory testing devices, sample taking is extremely limited as operations because of difficult preparation of specimen for testing the shape and construction from the target components. And the analytical method must be used in combination in order to establish the test conditions.

Generally, the RUL prediction of high-temperature components of power plant facilities can be divided into cases where there are no cracks and cases where there are cracks. In this research, creep and fatigue damage of steam turbine are evaluated under no-crack conditions considering the characteristic of rotating machine that a catastrophic accident occurs when a crack occurs.

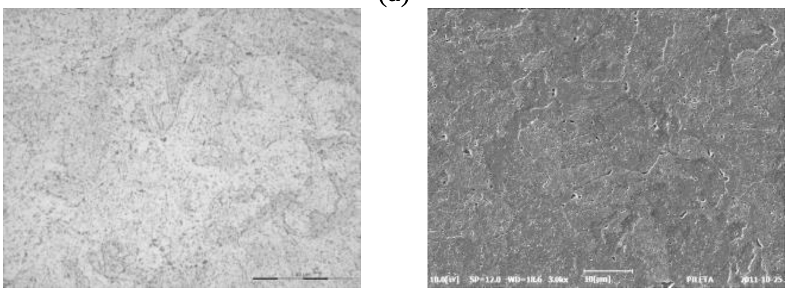
2.1.2 Nondestructive Method

Non-destructive techniques, such as replication analysis and hardness tests, can also be used to evaluate the damage rate. Replication analysis has been widely adopted to evaluate the damage rate of in-service steam turbines. It can be used to classify the level of material degradation in accordance with guidelines such as Neubauer or Vereinigung der Großkesselbesitzer e.V (VGB) [9, 10, 12-16].

Damage rates for steam turbines with ferritic steel have been determined by investigating the degree of micro-structural phase evolution, micro-void formation of grain boundaries, and evolution of carbides from visual inspection via scanning electron microscope (SEM) images [12, 17, 18]. Several elements (e.g., tubes, turbines, and pipes) have been studied to quantify damage via replication analysis. However, the replication method is based on five or six states; thus, results of its RUL prediction are classified as five or six states. Quantitative and accurate RUL prediction is relatively difficult [19]. For example, from the visual inspection of scanning electron microscope (SEM) image as shown in Figure 1, there was little difference in microstructures between highly-stressed and lowly locations. Because of the classification results from Figure 2-1, it is difficult to use them for RUL prediction of turbine as they are the relative results of qualitative damage rate from microstructure analysis. It would be desirable to quantitatively estimate RUL related to creep or fatigue damage rather than relying on a qualitative measure such as visual inspection from Optical Microscope (OM) or SEM images.



(a)



(b)

Figure 2-1 OM (X500) and SEM (X3000) image (a) highly-stressed location and (b) lowly-stressed location of 1Cr1Mo1/4V rotor steel after 146,708 hour operation

Rebound hardness test methods provide quantitative measures to evaluate the relative damage rate. These measures can be easily implemented, and measured hardness values can be calibrated with results from the conventional Vickers hardness test, which is only available in a laboratory setting [20]. Fujiyama et al. [21, 22] used hardness values as a correction factor to supplement empirical formulas (e.g., the Larson-Miller Parameter (LMP)) for RUL prediction that considers creep damage. Recently, Mukhopadhyay et al. [23] proposed a hardness-ratio-based creep life model that considers dislocation and precipitate phenomena.

However, in this approach, the predicted creep life can significantly deviate due to variations in temperature, as hardness values are combined with the LMP relation. Recently, instrumented indentation test methods were developed to measure strength in-situ. The indentation test is a non-destructive technique that determines material properties – including elastic modulus, tensile strength, and residual stress – by analyzing the indentation load-depth curve [24].

2.1.3 Analytical Method

For the RULs prediction of a turbine, the maximum stress or strain of the turbine should be calculated at the failure susceptible locations, respectively. In the analytical method, operating history, geometrical information of turbine, and thermal and material properties are used to calculate the stress, strain, and temperature distribution. Life assessment method of turbine components through experimental and finite element analysis is developed to predict fatigue life [25]. To perform accurate life calculation, a finite element analysis is carried out considering operation condition and characteristic of material behavior after modeling based on geometrical information [26]. The maximum stress and strain from finite element analysis (FEA) are reflected to life assessment of interesting facilities.

If a mathematical model or user-defined function about material behavior are defined, visco-plastic analysis can be carried out using finite element analysis [27] as shown in Figure 2-2. As seen from the Figure 2-2, the stress contour illustrates that the stress nearby the inlet notch and bore zone are significantly sensitive to the transient condition such as start-up. By FEA, calculate stress and strain results considering plastic behavior are used to determine creep and fatigue life by applying a life relation equation.

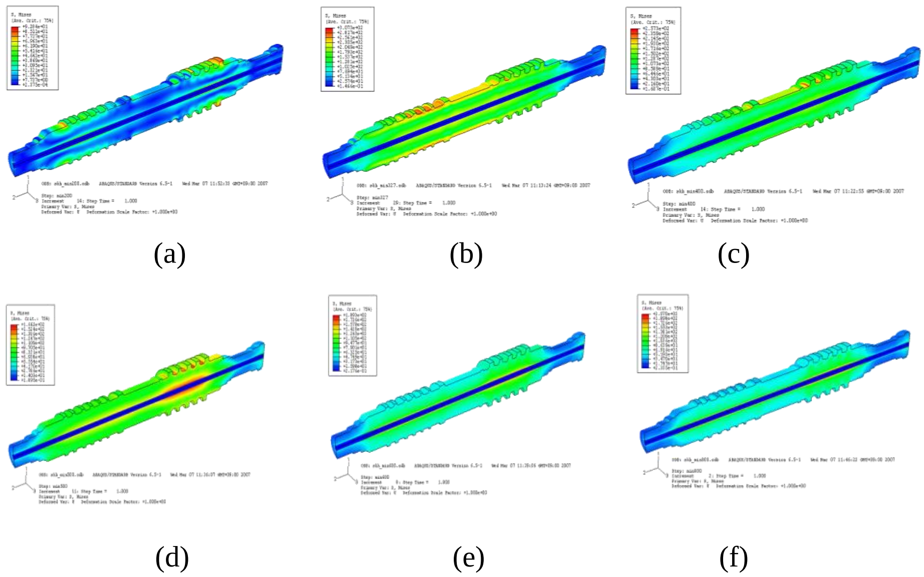


Figure 2-2 Contour of von Mises stress during start-up (a) rolling start (b) 127min (c) 200 min (d) 300 min (e) 400 min (f) 500 min [27]

Comparing elastic analysis, however, 3 dimensional visco-plastic analysis have some limitations such as long calculation time, convergence weakness. As an alternative, results of simplified elastic analysis or numerical analysis can be used to consider stress/strain concentration effects through the Neuber expression [28].

2.1.4 Summary and Discussion

The various RUL prediction methods previously described can be conveniently integrated into a phased approach with the three levels [29]. Since the destructive methods are not applicable for continuously operated key component (turbine) in power plant, non-destructive or analytical methods are relatively easy to predict RUL and those methods are useful to apply to the plant site.

However, it is necessary to understand the characteristics of each method and obtain sufficient information for more accurate RUL predictions, respectively. Therefore, the characteristics and uncertainties of the nondestructively measured data should be quantitatively analyzed. Related with analytical method, it is necessary to determine the dominant damage model directly related to the RUL and calculate accurate damage rate without the complexities and high costs.

2.2 Data-driven and Model-based RUL Prediction

In general, prognostic approaches can be classified into three categories: 1) model-based approaches [30-32]; 2) data-driven approaches [33, 34]; and 3) hybrid approaches [35]. Data-driven approaches use a system health knowledge learned from system behavior data. These are mainly based on massive sensory data with reduced requirements for knowing inherent system failure mechanisms. On the other hand, model-based approaches use mathematical or empirical models that represent system degradation. Such approaches based on the understanding of physics of failure and underlying degradation models. Hybrid approaches combine data-driven and model-based methodologies [36, 37]. A good review of hybrid prognostic approaches was given in [37]. The hybrid prognostic approaches mentioned in the above literature survey can mainly be categorized into five types through the combination of Experience-based model, data-driven model and physics-based model. Sparse literature has mentioned the practices of using the hybrid approach since there are some challenges even though it is potentially beneficial to fuse all types of information.

Data-driven and model-based prognostic approaches are compared and summarized with recent examples in Table 2-2.

2.2.1 Data Driven Approach

Data-driven approaches derive predictive models from routinely collected monitoring data [38]. It is usually based on statistical, machine learning, and neural network methods. Though those are necessary to require failure data for training, such approaches are better to predict the RUL in the system-level without physical knowledge.

Table 2-2 Comparison of data-driven and model-based prognostics approaches

	Data-driven approach	Model-based approach
Definition	To use a system health knowledge learned from system behavior data	To use mathematical/empirical models that represent system degradation
Pros	· Better to predict RUL at the end of life · Applicable to system level · Taking into account uncertainties in sensing / operation condition	· Possible to assess RUL in early stages · Applicable for Virtual qualification - stress calculation by FEA
Cons	· Need to build training data · Application-specific · Failure data needed	· Need to understand physics of failure · Information lacking in many physical parameters · Applied to component level
Examples	· RUL prediction for Cooling fan [6] · RUL prediction for bearing using ANN [28, 39] · RUL prediction for Turbofan, battery using Bayesian approach. [29] · To predict fatigue crack growth rate using NN [40]	· Forecasting the rate of defect growth on a bearing [41-43] Prognosis for aircraft actuator/bearing [42, 44] · Prognosis for cracked rotor shaft [45] · RUL prediction of OLED [46]

2.2.2 Model based Approach

As described in Section 2.2, Model-based approaches are usually based on empirical or physical model describe the degradation process of the components. For example, Paris's law was used to predict the rate of crack growth on a complicate system [43, 52]. Though such approaches require specific domain knowledge related with physics of failure, it is possible to assess the RUL in early stage. As practical engineered system generally consist of multiple components with multiple failure modes, understanding all potential physics of failure and their interaction for a complex system is almost impossible [57]. In practice, even when the model of the degradation process is known, the RUL estimate may be difficult since the degradation state of the system may not be directly measured and the measured data may be affected by various uncertainties.

In this study, empirical model-based approach is based on statistical and machine learning methods that aim at discovering the turbines' degradation using off-line measured data instead of the on-line sensory data. And physical model-based approaches build creep and fatigue damage models describing the degradation of steam turbine and consider their interaction effects.

2.3 Empirical Model-based RUL Prediction

2.3.1 On-site Data Measurement

Non-destructive techniques, such as replication analysis and hardness tests, can also be used to evaluate the damage rate. Replication analysis has been widely adopted to evaluate the damage rate of in-service steam turbines. It can be used to classify the level of material degradation in accordance with guidelines such as

Neubauer or Vereinigung der Großkesselbesitzer e.V (VGB) [9, 10, 12-16]. Damage rates for steam turbines with ferritic steel have been determined by investigating the degree of micro-structural phase evolution, micro-void formation of grain boundaries, and evolution of carbides from visual inspection via scanning electron microscope (SEM) images [12, 17, 18]. Several elements (e.g., tubes, turbines, and pipes) have been studied to quantify damage via replication analysis. However, the replication method is based on five or six states; thus, results of its RUL predictions are classified as five or six states. Quantitative and accurate RUL prediction is relatively difficult [19]. For example, there was little difference in microstructures between low-stress and high-stress locations. Likewise, the hardness at the locations shows relatively little difference. Since it is difficult to use these results to quantify the health conditions from visual inspection of optical microscope (OM) or SEM images, a quantitative measure is appropriate to predict RUL related to creep or fatigue damage rather than qualitative measures.

Rebound hardness test methods provide quantitative measures to evaluate the relative damage rate. These methods can be easily implemented, and measured hardness values can be calibrated with results from the conventional Vickers hardness test, which is only available in a laboratory setting [20]. Fujiyama et al. [21, 22] used hardness values as a correction factor to supplement empirical formulas (e.g., the Larson-Miller Parameter (LMP)) for RUL prediction that considers creep damage. Recently, Mukhopadhyay et al. [23] proposed a hardness-ratio-based creep life model that considers dislocation and precipitate phenomena. However, in this approach, the predicted creep life can significantly deviate due to variations in temperature, as hardness values are combined with the LMP relation. Recently, instrumented indentation test methods were developed to measure strength in-situ. The indentation test is a non-destructive technique that determines material properties – including elastic modulus, tensile strength, and residual stress – by analyzing the indentation load-depth curve [24].

Despite its potential advantages, to date, a very limited amount of scientific work has been conducted in the research area of damage rate evaluation or RUL prediction of in-service components [47-49]. Also, there is almost no actual measurement data available from indentation testers that include operating time.

2.3.2 Bayesian Inference

The traditional linear least square method can be used to identify deterministic parameters when the model is a linear function of the parameters. This method is in particular powerful when many data are available [50]. On the other hand, Bayesian approaches have been widely used to address uncertainty for model-based prognostics with pre-existing model though it is computationally expensive in case of multi-dimensional integration. It can take into account the prior knowledge on the unknown parameters and improve it using experimental observations. For example, Guan et al. [51] proposed a general framework for probabilistic prognosis using maximum entropy approach with the classical Bayesian method for fatigue damage assessment. Dawn et al. [52] used Bayesian inferences with the MCMC algorithm to estimate fatigue and wear damage. More recently, Chiachío et al. [53] presented a Bayesian approach to update model parameters of existing fatigue models for composites. Compare et al. [54] proposed a semi-Markov degradation model based on expert knowledge and few field data within the Bayesian statistical framework. In the previous Bayesian approaches, the correlation between hyper-parameters and uncertainties of damage model's parameters was not accounted for. To the best of our knowledge, this study is the first attempt to define a damage threshold for steam turbines to execute an RUL prediction.

2.3.3 Summary and Discussion

As a one of nondestructive methods, however, the hardness measurement method that is most commonly and easily used in actual field settings is used for RUL prediction. Nonetheless, RUL predictions based on the rebound hardness test method are subject to uncertainties. Those uncertainties are due to aleatory and epistemic uncertainties in irregular and discontinuous measurement and non-homogeneous samples. In this study, sporadically measured hardness is random due to the uncertainty that arises from the heterogeneity of turbines in terms of manufacturers, sizes, operating conditions, sites, etc.

Since Bayesian approaches have been used to address uncertainty [55, 56], in particular, discrepancy reduction and a damage growth model that considers uncertainties should be developed for accurate RUL prediction of aged components in power plants. If there is a suitable damage growth model with parameters, also, the correlation between parameters and uncertainties of damage growth model's parameters should be accounted to execute an RUL prediction.

2.4 Physical Model-based RUL Prediction

2.4.1 Creep or Fatigue Damage Model Analysis

The development of creep-fatigue damage in high-temperature components steel of power plant depends on temperature, strain range, strain rate, hold time, and the creep strength and ductility of the material [58-62]. A RUL prediction of steam turbine at creep-fatigue conditions is usually performed using the life fraction rule [63-66]. The creep-fatigue resistance of power plant steels may be characterized in terms of different parameters depending on whether the component evaluation interest is defect-free or defect assessment [67].

Creep damage model based analysis

Tremendous research efforts have been devoted to investigate creep behavior for high temperature materials. Most of the studies carried out in the 1980s were based on the Norton-Bailey relation [68] which is based on Arrhenius equation. Also, various empirical equations; θ-projection model [69], Graham-Walles model [70], and modified Graham-Walles model [71] were proposed through creep rupture test. However, those models are not appropriate to estimate lifetime since a too many parameters are required or the creep behavior can be only analyzed in a certain ranges.

Thus, the Larson-Miller parameter [72] is commonly used to predict the creep failure time since it can be easily applied using limited test data. Recently, a probabilistic methodology is proposed to assess life of high-temperature components there are very wide scatter present in creep and creep failure data. As a representative example, Monte Carlo technique and the standard damage fraction by creep damage are proposed for piping system under creep conditions [73].

Fatigue damage model based analysis

Low cycle fatigue(LCF), considered in this research, is defined as the fatigue mechanism that controls failures occurring at $N < 10^4$ cycles and typically is of concern when there is significant cyclic plasticity [74]. In transient or dynamic environments, stresses in high-temperature components constantly vary, making low cycle fatigue failure a critical issue when designing or operating these components [75].

Since there are no fundamental differences between the mechanisms of the low cycle fatigue and the high cycle fatigue, S-N curves based on LCF tests are easily used to estimate crack initiation time as a fatigue life. Especially, curves of strain amplitude and cyclic life obtained in LCF tests can be separated into elastic and plastic strain ranges. Therefore, Coffin and Manson relation, which is composed of two types of power functions, is commonly used to predict fatigue life for high-temperature components.

2.4.2 Creep-Fatigue Damage Summation Model-based Analysis

In the past years, many researchers have made great efforts to evaluate the creep-fatigue damage in terms of new analyses, new models, and theoretical considerations with respect to the creep and fatigue coupled conditions. Among the various methods of simultaneously considering creep and fatigue, Miner's linear damage accumulation method was a dominant approach to analyze the creep and fatigue damage assessment due to its simplicity. The damage based on linear cumulative damage rule under creep-fatigue load is generally used to predict lifetime or risk of power plant components: rotor, casing and valve etc [8, 25, 76-80]. By the linear accumulation of creep and fatigue damage, especially, a nonlinear continuum damage mechanics (CDM) model is proposed to assess the creep-fatigue life of steam turbine rotor [81] and fatigue interaction model by the inelastic strain energy density is developed to represent the damage accumulation under stress control mode [82].

Recently, linear and bi-linear damage loci is used to classify safe and unsafe region [67] and torsional vibration damage is linearly added with creep and fatigue damage [26]. Compared with the nonlinear accumulation method, however, Miner's method is often over evaluated and it is not applicable if different kinds of damages are partially overlapped in a section [83]. If the two types of damages are independent with each other and there is no overlap between the creep and fatigue damage, creep and fatigue damages can be linear superposition directly. However, the traditional linear damage accumulation method causes repeated calculation about the overlapping parts and it is no longer applicable if the creep and fatigue damage have overlapping parts which are not independent [84].

Table 2-3 summarizes some creep-fatigue life prediction methods that were developed since 1970. Those methods are all empirical, based on phenomenological framework. Among the life prediction methods, damage summation, strain range partitioning and damage approach are widely used to some extent for various applications. However, there is a little systematic scheme to predict RUL considering actual system and loading conditions.

Table 2-3 Summary of creep-fatigue life prediction methods and equations

Method of life prediction	Life prediction equation	Material parameters needed (number)
Linear life fraction [1, 65, 81, 85, 86]	$\sum N/N_f + \sum t/t_r$	Strain-life data (4) creep-rupture (2~4)
Nonlinear life fraction [81, 87]	$\sum N/N_f + \sum t/t_r \; + e\left[\sum N/N_f \cdot \sum t/t_r\right]^r$	Strain-life data (4) creep-rupture (2~4) interaction term (2)
Strain range partitioning [88]	$N_{ij} = A_{ij}\Delta\varepsilon_{ij}^{0jk}$, ij~PP, PC, CP, CC loops (P: Plastic, C:Creep)	Four inelastic strain vs. life relations (8)
Generic model [89]	$N_f = function(S, R, T, H)$ (S:strain range, R : strain rate, T:temperature, H : hold time parameters)	Hyper-parameter (71)
Damage growth model [90]	$D(\mathrm{t}) \sim \mathrm{N}(\mu_D(t), \sigma_D(t))$	Hyper-parameter of mean and standard deviation (4)

On the other hand, in case of fatigue damage, there are lots of researches about nonlinear fatigue damage accumulation model which is not combined with creep damage, since individual damage due to various loads must be added. The nonlinear fatigue damage accumulation models can be classified into the following approaches: damage curve based approaches [88, 91], continuum damage mechanics models [92-95], energy based methods [96-98], physical properties degradation based model [96, 99].

Online & multi-damage life estimation of steam turbine

To calculate a low cycle fatigue damage, online monitoring model of a 300MW steam turbine rotor is introduced using finite element analysis, transfer function and continuum damage model [100-102]. And a polynomial control performance assessment method is developed using nonlinear low cycle fatigue damage model [103]. In recent years, artificial neural network methods are used to evaluate multi-damage life [84, 104] or to control the steam turbine heating process as one of the recommendations for stable operation [105].

However, these were mainly focused on the investigation of only damage behavior or the assessment of life expectancy of components without considering interaction effects with operation mode and type of damage for the actual steam turbine in operation.

2.4.3 Summary and Discussion

A lot of researches have been published for a long time to estimate the lifetime by creep and fatigue damage of high-temperature components.

When the steam turbine is subjected to different damages such as creep and fatigue damage, typical linear superposition is not applicable. Because the different damages have overlapping parts on the failure susceptible locations of steam turbine.

Thus, advanced methodologies to predict the RUL of steam turbine under the creep and fatigue damage coupling should be developed and replaces the simple summation of multiple damage coupling. Because acceleration of start-ups causes to increase life consumption of steam turbines and change of operating mode affects the interaction effect of the multiple damage interaction.

Chapter 3

A Practical RUL Prediction Framework of Steam Turbine with FMEA Analysis

As mentioned in the literature review, many research efforts have been devoted to the RUL prediction of steam turbine. To the best of the author's knowledge, previous researches have not been able to systematically organize step-by-step procedure, but those are tendency to bias how the calculations are carried out accurately in each step.

The remainder of Chapter 3 is organized as follows. Section 0 describes the overview of steam turbines. The results obtained by FMEA (Failure Mode and Effects Analysis) for steam turbine are discussed in Section 3.2. In Section 3.3 and 3.4, measured data-driven approach for offline prediction and damage model based approach for online prediction are briefly explained, respectively. Finally, the conclusions of this work are provided in Section 3.5.

3.1 Overview of Steam Turbines

A conventional power plant consists of boiler, steam turbine and generator, and other auxiliaries as shown in Figure 3-1. Boiler generates steam at high pressure and high temperature. Turbine is an engine that converts energy of fluid into mechanical energy. Generator converts the mechanical energy into electric power. Steam turbines are machines that are used to generate mechanical (rotational motion) power from the pressure energy of steam. Steam turbines are one of the most popular power generating machines used in the power industry. They are widely used because water is prevalent, boiling points are moderate, and the operating cost is reasonable. Steam turbines are machines that convert thermal energy from hot and pressurized steam to mechanical (rotational motion) work. Steam turbines are designed to improve thermodynamic efficiency by adopting multiple stages to expand steam [106]. As shown in Figure 3-2, high-pressure parts of steam turbines consist of (1) a casing or shell that is usually divided at the horizontal center line and contains the stationary blade system; (2) a rotor carrying the moving buckets (blades or vanes) either on wheels or drums, with journal bearings at the ends of the rotor; (3) a set of bearings attached to the casing to support the shaft; (4) a coupling to connect with the driven machine; and (5) pipe connections to the steam supply at the inlet and to an exhaust system at the outlet of the casing or shell.

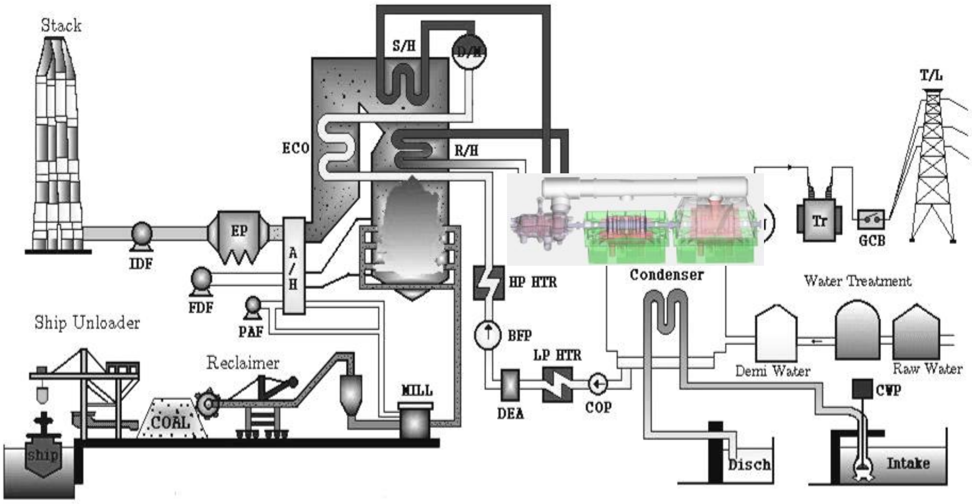


Figure 3-1 Schematic of coal-fired power plant

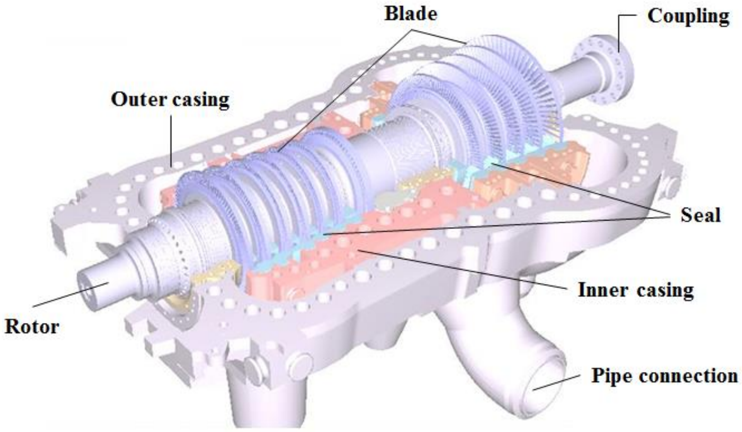


Figure 3-2 Schematic of a steam turbine (high and intermediate pressure parts)

3.2 FMEA for Steam Turbines

For high-pressure (HP) portions, typical failure events are creep induced deformation, thermo-mechanical fatigue cracking and steam flow induced erosion. For low pressure (LP) portion, typical failure events are environmental assisted fatigue cracking and steam flow induced erosion. The features of events are described as follows for major component. A steam turbine can be divided into many components, and the life cycle event tree is used for describing the chain action of one component failure leading to another component failure. It is well known that degradation by creep and fatigue damage is dominant failure modes of steam turbine major components [27, 107].

Failure mode and effect analysis (FMEA) is a structured approach to identifying the ways in which a product or process can fail and to prioritizing the actions that should be taken to reduce risk. Although there are still many doubt about the methodology, FMEA has been successfully accepted in many different fields [108]. Failure mode and effect analysis (FMEA) of steam turbines was conducted over twenty years in the electric power industry; results are shown in Table 3-1. FMEA qualitatively shows the occurrence, severity, and risk of key components in a steam turbine. From the viewpoint of material and mechanical properties, softening and reduction in the strength of forged part such as rotor, blades, bolts, casings and valves are caused by creep or fatigue due to long term high temperature, stress and/or many start-ups and shut-downs. Among the many turbine components, this study looks specifically at the HIP rotor for RUL prediction due to its high risk. Creep and low/high cycle fatigue (LCF/HCF) are known to be the dominant failure mechanisms of steam turbines [27, 107]. High temperatures and centrifugal force causes creep damage in high-stress regions, such as bore and wheel hooks. Thermo-mechanical fatigue damage from the thermal cyclic load causes cracking at the wheel corner [1, 22, 107]. Material degradation related to damage in the turbines, such as low-cycle fatigue and creep, leads to unexpected breakdown and economic losses in the electric industry. Since creep and fatigue damage does not occur independently, this research classifies the steam turbine rotor into a bore part and 1st stage surface part to calculate the RUL under creep-fatigue interaction damage.

Table 3-1 FMEA results for a steam turbine

Component	Failure cause	Failure mechanism	Failure mode	Occurrence	Severity	Risk
HIP(High-Intermediate Pressure) steam turbine						
Rotor	Temp. cycling	Creep, LCF	Fracture	Not often	Very high	High
HP blade	Temp. cycling	LCF, HCF	Failure	Not often	High	Moderate
HP casing	Temp. cycling	CREEP, LCF	Crack	Not often	Moderate	Moderate
IP blade	Temp. cycling	LCF, HCF	Failure	Not often	High	Moderate
IP casing	Temp. cycling	CREEP, LCF	Crack	Not often	Moderate	Moderate
LP(Low Pressure) steam turbine						
Rotor	Wet. Cycling	Corrosion, LCF	Fracture	Not often	High	High
Blade	Wet. Cycling	LCF,HCF, Corrosion	Failure	Often	Moderate	Moderate
Bearing	Wear	Wear	Vibration	often	Low	Moderate

3.3 A Framework for RUL Prediction of Steam Turbine

The overall framework for RUL prediction of steam turbine is shown in Figure 3-3. The procedure is largely composed of the empirical model-based and physical model-based approaches.

In the empirical model-based process, sporadically measured data are acquired from turbine units. To acquire material hardness data of both healthy and aged conditions from the same turbine, the wheel corner of the 1st stage of the turbine rotor was selected as an aged location. The groove of the exhaust section was chosen as the healthy location. Since measurement data are subject to various sources of uncertainty, such as variability in material properties, measurement locations, surface conditions, and testing operators, it is necessary to exclude physically meaningless values from distributed data sets. Next, damage indices from

Next, a hypothesis test is performed using limited observed data to see if the assumed distribution model is sufficiently productive to integrate into a single metric for a damage growth model. An area metric and the u-pooling method [109] are employed for the hypothesis test to assess the global predictive capability of a model. A Bayesian inference technique can be used to estimate the probability distribution of the damage index from on-site measurements. As more measurement data are integrated into the updating process, hyper-parameters of damage growth model are updated. Finally, RUL can be predicted by subtracting the PDF of the damage index from the threshold by using the mean and standard deviation distribution.

The steam turbine is fully assessed in terms of the external thermos-mechanical boundary conditions imposed during the operating time, and these are used in conjunction with material constitutive equations to define the distribution of stress and strain throughout the structure. In case of physical model-based method, on the other hand, failure susceptible locations (bore and 1st stage surface) of turbine rotor, damage mechanisms, and essential parameters related with life are determined. In this research, necessary parameters are defined as stress and strain values by under the steady (base-load) and unsteady (peak-load) operation conditions of the specific plant and statistically calculated. Next, creep and fatigue damage rate are determined by reference to the material test data from creep and fatigue test. As more damage rates are integrated into the updating process, hyper-parameters of creep-fatigue damage interaction model are updated. If operating hour or the number of cycles for target system is obtained from operation history, finally, remaining useful life is determined by the time or number of cycle. The creep and fatigue damage rates are finally compared with the crack initiation locus in a creep-fatigue damage diagram and the risk of failure assessed.

Table 3-2 and Table 3-3 details the empirical and physical model-based RUL prediction framework with the seven steps, respectively. STEP 2 to STEP 6 can be repeated to update the RUL distributions as new measured or online data sets are acquired. In the next Chapter 4 and 5, the RUL of steam turbine is calculated by data-driven and model-based approaches according to the procedure in Figure 3-2 and Figure 3-3.

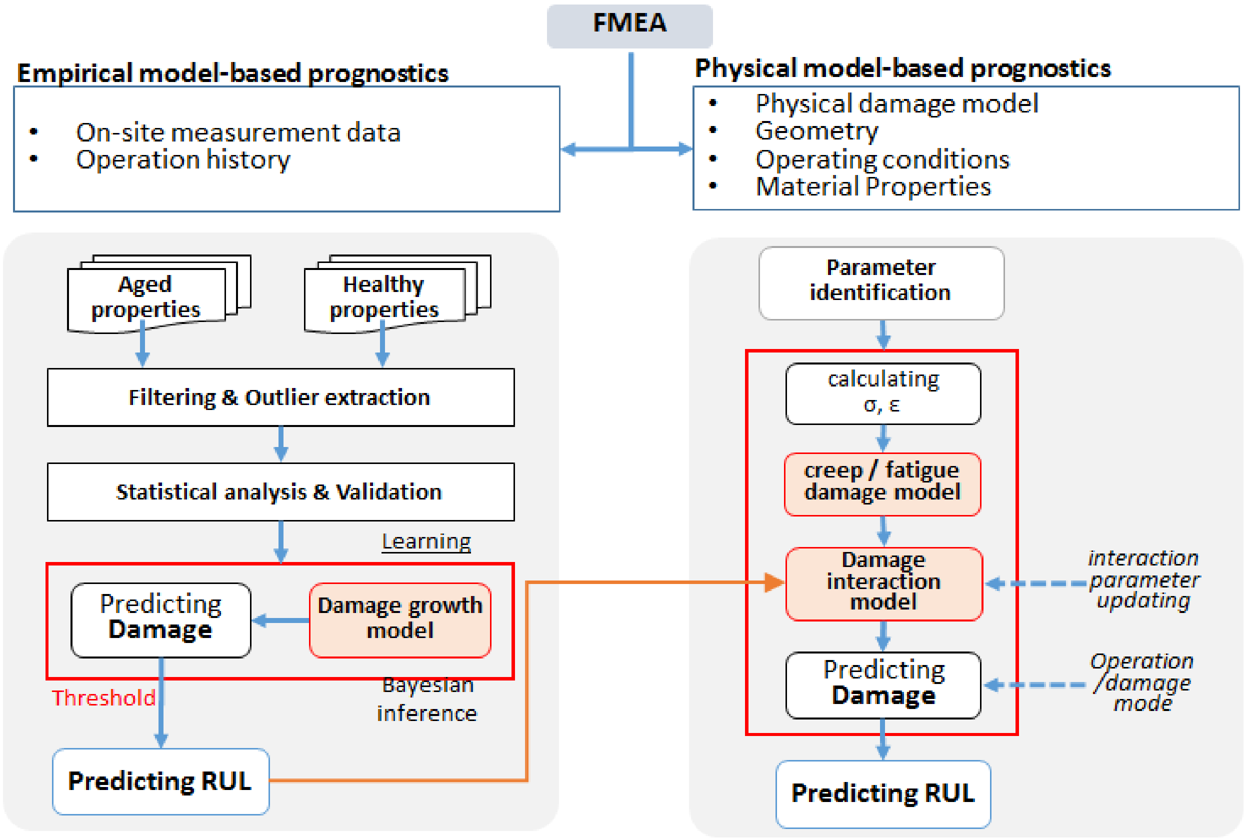


Figure 3-3 A framework for RUL prediction of steam turbines applicable to various data types

Table 3-2 Procedure of the empirical model-based RUL prediction framework

STEP 1	To define the measured data driven RUL prediction problem
STEP 2	To acquire hardness data sets from highly-aged and lowly-aged location ;
STEP 3	To filter and extract outlier from measured data set
STEP 4	To analyze statistically to determine distribution of data set To valid estimated distribution by U-pool method
STEP 5	To update damage growth model using Bayesian inference
STEP 6	To determine the threshold considering design life
STEP 7	To predict the RUL predictions using damage growth model which employs newly added data set

Table 3-3 Procedure of the physical model-based RUL prediction framework

STEP 1	To define the damage model based RUL prediction problem
STEP 2	To perform FMEA analysis and acquire loading signal from operation data
STEP 3	To identify parameter from selected damage model
STEP 4	To calculate steady state stress for creep damage model and transient state strain for low cycle fatigue damage model
STEP 5	To calculate creep and fatigue damage for steam turbine, statistically
STEP 6	To update hyper-parameter of mode-dependent damage interaction model
STEP 7	To predict the RUL prediction using

3.4 Summary and Discussion

This chapter presented the RUL prediction framework for steam turbine. The framework is composed of two approaches: measured data driven and damage model based methods. The proposed RUL prediction framework with uncertainty quantification enables the statistical prediction of RULs.

In this model-based RUL prediction framework, (1) When the hardness values can be obtained in a sporadic maintenance schedule, the RUL and uncertainty can be calculated by the empirical model-based procedure regardless of the type of turbine; (2) If it is possible to obtain real-time operation data such as temperature and damage model, on-line RUL prediction is possible according to the physical model-based procedure.

The key to success in this effort is to quantify and reduce uncertainties of predicted RUL results considering different purpose such as off-line and/or on-line prediction.

Chapter 4

A Bayesian Approach for RUL Prediction of Steam Turbine with Damage Growth Model

This research presents a Bayesian approach to a new damage growth model that can utilize sporadically measured and heterogeneous on-site data from steam turbines. A hardness-based damage index is selected as a damage indicator to evaluate the damage rate. Using this, a new damage growth model is proposed as a function of operating time. Sporadically measured hardness is random due to the uncertainty that arises from the heterogeneity of turbines in terms of manufacturers, sizes, operating conditions, sites, etc. Therefore, the mean and standard deviation of the damage index are predicted considering the parameters' correlation and the distribution can be identified simultaneously by using Bayesian inference [55] and MCMC simulation. The predicted damage growth results from the Bayesian and nonlinear regression method are compared and validated using actual field data from ten turbine units.

The remainder of the Chapter 4 is organized as follows. Section 4.1 presents sporadically measured and heterogeneous on-site data with uncertainties and damage indices are explained in Section 4.2. Section 4.3 focuses on the damage growth model using the Bayesian updating method and MCMC simulation. Section 4.4 presents the RUL prediction results of Bayesian and the nonlinear least square (Nlsq) method. A damage threshold is proposed to determine design life, the proposed methodology is validated, and the RUL distribution for an aged steam turbine is predicted based on the proposed damage growth model. Section 4.5 presents the conclusions of the research.

4.1 Characteristics of On-site Measurement Data

It is extremely difficult to measure material degradation directly. Destructive analysis is available only in well-controlled laboratories, while non-destructive analysis (i.e., the replication method) is limited in its ability to accurately predict the damage rate or RUL.

This research employed a rebound hardness tester (Leeb hardness tester in accordance with DIN 50156-1 and ISO/FDIS 16859-1) because of the need for on-site and non-destructive measurement. The load of the handheld probe of the hardness tester was 10 kgf. This study used Vickers hardness values. The hardness data are subject to uncertainty due to inconsistency in turbine targets, measurement locations, and testing operators [110]. To take into consideration the uncertainty effect, a set of measurement data were collected from ten turbine units: five base-load and five peak-load units. More than five repeated data measurements from each turbine were used in this study, as prior work showed that between 3 and 10 measured hardness data points are generally acceptable [111].

It is well known that virgin rotors and the low-temperature regions of the retired rotors have almost the same microstructure, consisting of finely dispersed carbide precipitates and densely distributed dislocations [112]. Within the turbine rotor, therefore, the hardness in a low-temperature region can be used as a reference hardness. Figure 4-1 shows two different types of a steam turbine; typical base-load and peak-load steam turbines. To acquire material hardness data of both low-stress and high-stress conditions from the same turbine, as shown in Figure 4-1, the wheel corner of the 1st stage of the turbine rotor was selected as a high-stress location. The groove of the exhaust section was chosen as the low-stress location. Steam turbines have different overhaul periods and schedules. Ten sets of the hardness data set, which were sporadically measured at overhauls over 10 years, are shown in Table 4-1. Thus, hardness data sets from both low and high-stress locations were arranged according to the equivalent operating hours (EOH). For both base-load or peak-load turbines, EOH can be calculated by using actual operating hours, the number of starts, and life factor as [113]

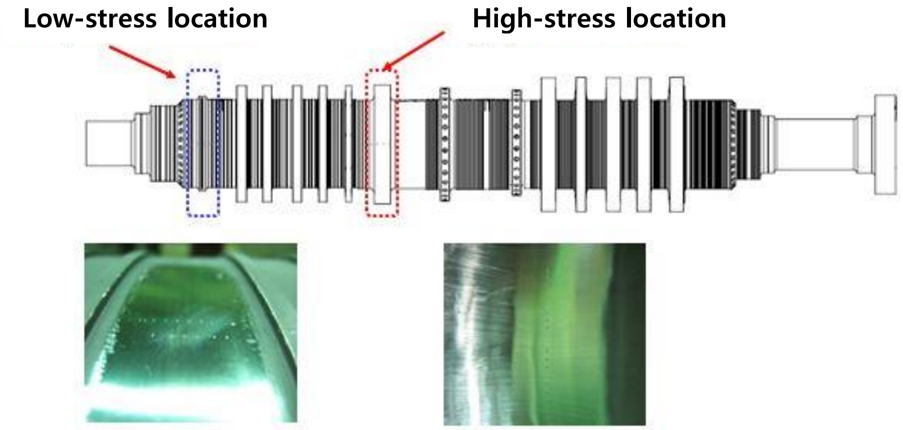
$$EOH = t_{op} + (LF \times N_{op}) \tag{4-1}$$

where t_{op} is the actual hours of operation, N_{op} is the number of starts, and LF is the life factor.

Development of a damage growth model that utilizes on-site hardness data encounters two major hurdles: (a) heterogeneity and (b) uncertainty in data. First, data can be collected during scheduled major overhauls in accordance with the maintenance strategy of the particular power generation company. Major overhauls are typically executed every four years and involve the complete disassembly, inspection, and reassembly of the steam turbine. In practice, sporadically measured data are also acquired from turbine units. Turbine units in coal power plants run at the base load continuously throughout a year, while peak-load turbines in a combined cycle power plant generally run only during periods of peak demand for electricity [114]. Based on these factors, turbine units operate with different fuel sources and power outputs, as shown in Table 4-1. Second, measurement data are subject to various sources of uncertainty, such as variability in material properties, measurement locations, surface conditions, and testing operators [115, 116]. Even if turbines are made of the same material, the strengths of different turbines are different. In addition, the operator also represents a potential source of error related to testing conditions. Slightly mismatched measurement locations and/or different handling of the instrument may occasionally lead to deviations in the results.

In Table 4-1, H_a signifies the hardness at high-stress locations and H_v represents hardness at low-stress locations. These values are distributed, which means that uncertainty from sporadic measurements in heterogeneous turbines exists for each data set. Since the measured hardness is indirectly related to strength, the damage rate can be quantified and damage growth can be predicted for RUL calculation. In this research, a damage growth model that uses a hardness-based damage index is proposed in Chapter 4.3.

To develop the damage growth model in this setting requires the use of heterogeneous and sporadic measurement data.



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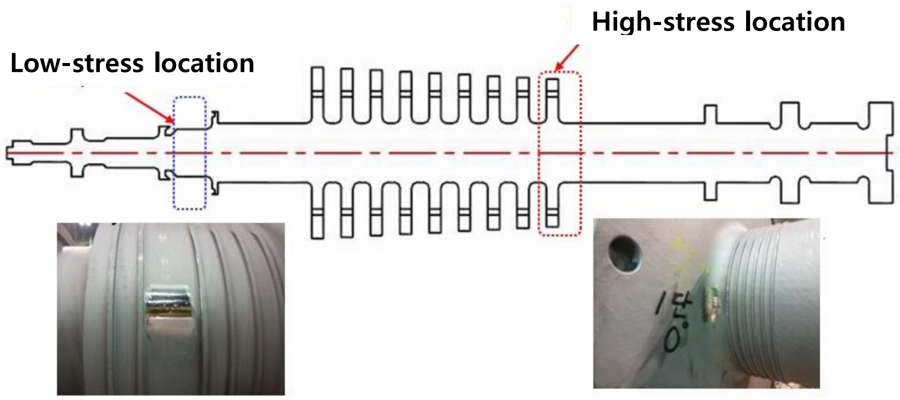


(b)

Figure 4-1 Measurement locations for material properties of turbines (a) steam turbine of base-load power plant and (b) steam turbine of peak-load power plant

Table 4-1 Hardness data for ten turbine units

Plant Unit		A1	B6	C2	B6 (replaced)	B3	D1 (retired)	E2	F1	G4 (retired)	H5 (retired)
Output (MW)		500	500	500	500	500	200	182	350	200	200
Load		Base					Peak				
Fuel		Coal	Coal	Coal	Coal	Coal	Oil	NG	Oil	NG	NG
EOH (hrs.)		74,327	95,097	115,671	146,708	157,995	186,478	201,671	212,522	213,175	255,288
Ha	#	5	10	5	17	9	10	20	10	9	5
	Mean	260.0	241.1	260.5	251.6	241.7	260.1	222.0	237.8	243.5	222.0
	St. dev.	3.34	4.01	4.87	3.99	5.35	4.34	4.96	3.43	5.79	6.28
Hv	#	5	10	5	17	9	10	20	10	9	5
	Mean	263.0	245.7	265.8	258.8	249.3	271.6	236.1	261.9	267.8	272.8
	St. dev.	2.49	2.41	3.18	3.18	5.70	1.78	5.31	4.72	5.70	5.10

EOH : Equivalent Operating Hours

4.2 Measured Data based Damage Indices

Eight damage measurement methods and damage indices are compared in Table 4-2 [117]. Most damage measurements are destructive; thus, they are not suitable for in-service facilities and have limitations in their ability to consider both creep and fatigue damage. Among non-destructive methods, it is relatively easy to measure material hardness from actual steam turbines. Moreover, hardness is more sensitive to damage than the replication method due to the softening effect of damage [20]. From Table 4-2, thus, this study makes use of hardness data to define a hardness based damage index that takes into account both creep and fatigue damage as [117]

$$D = 1 - \widetilde{H}/H = 1 - H_a/H_v \tag{4-2}$$

where H_a and H_v are the hardness values measured at aged (or damaged) and virgin (or undamaged) material states, respectively, using the Leeb hardness test. The hardness at the aged state is measured in a high-stress region (H_a), while the one at the virgin state is measured in a low-stress region (H_v), as shown in Figure 4-1. Figure 4-2 illustrates the box plots of measured hardness at different operating hours. Although the spread in the levels of hardness are not the same, the difference between high-stress and low-stress hardness increased. Due to

Table 4-2 Damage index by direct damage measurement

Damage measurement	Damage Index	Creep	Fatigue	Etc
Hardness	$D = 1 - \tilde{H}/H$	Normal	Good	Non-destructive
Elasticity modulus	$D = 1 - \tilde{E}/E$	Good	Good	Non-destructive
Density	$D = (1 - \tilde{\rho}^2/\rho)^{2/3}$	Bad	Bad	Destructive
Ultrasonic waves	$D = (1 - \tilde{v}^2/v)^{2/3}$	Normal	Bad	Destructive
Cyclic stress amplitude	$D = (1 - \Delta\sigma^*/\Delta\sigma)$	Bad	Normal	Destructive
Tertiary creep	$D = 1 - \left(\dot{\varepsilon}_{\mathrm{p}}^*/\dot{\varepsilon}_{\mathrm{p}}\right)^{1/j}$	Good	Bad	Destructive
Electrical resistance	$D = 1 - \tilde{V}/V$	Normal	Bad	Destructive
Micrography	$D = \partial S_{\mathrm{D}}/ \partial S$	Normal	Bad	Destructive

previously mentioned uncertainties, hardness data are statistically distributed so that the probability density functions (PDF) of the damage index are shown in Figure 4-3 at different operating hours. Since damage indices are able to track the progress of damage with operating hours, distributed damage indices based on hardness can be used to develop a damage growth model for RUL prediction.

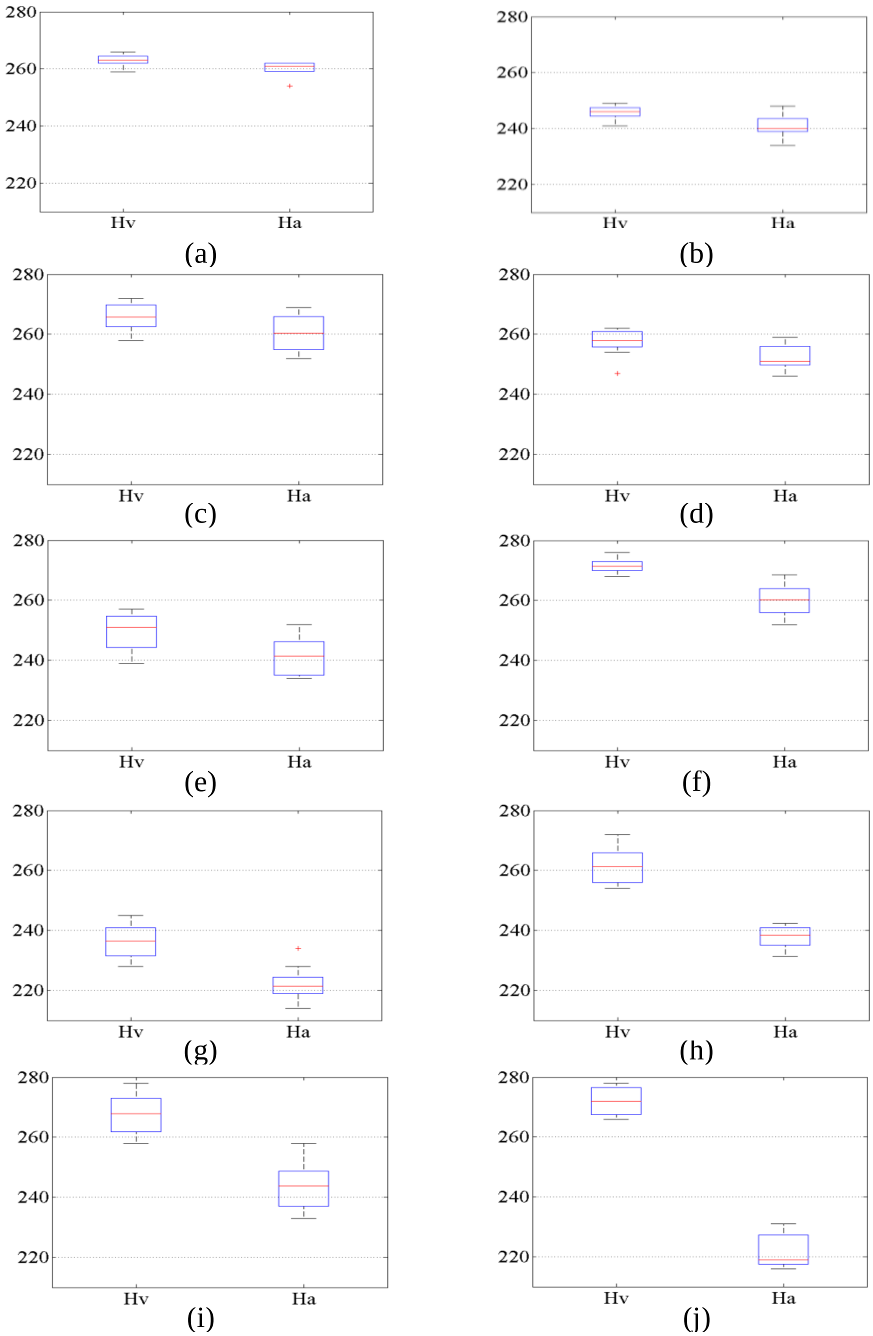
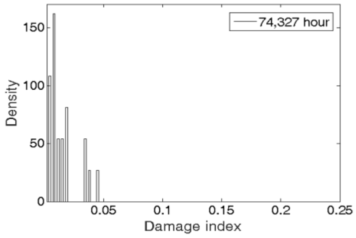


Figure 4-2 Comparison of hardness; box plots by operation time (a) 74,327 hours, (b) 95,097 hours, (c) 115,671 hours, (d) 146,708 hours, (e) 157,995 hours, (f) 186,478 hours, (g) 201,671 hours, (h) 212,522 hours, (i) 213,175 hours, and (j) 255288 hours



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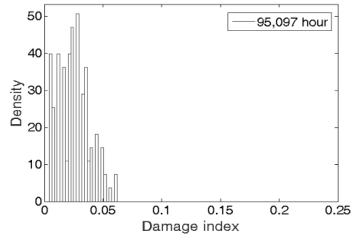

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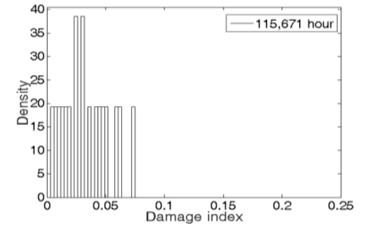

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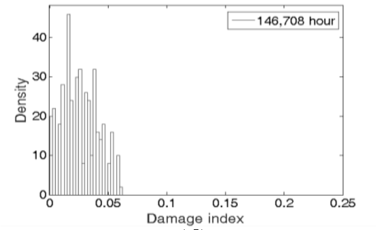

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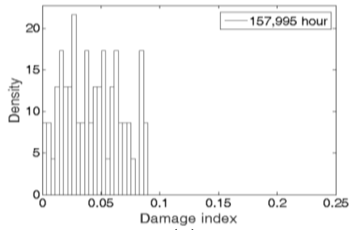

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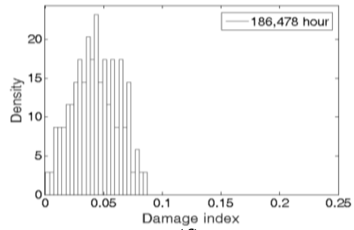

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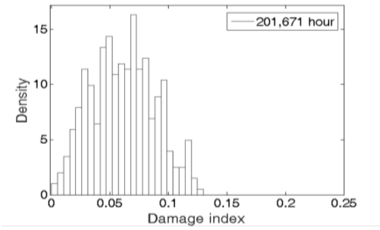

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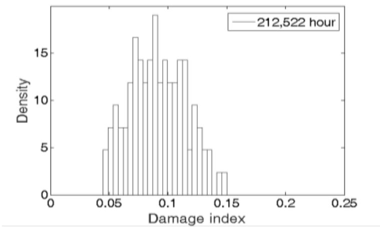

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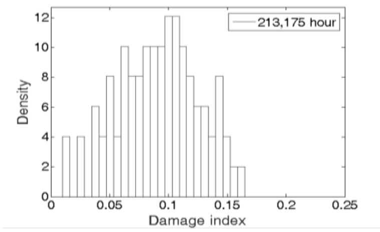

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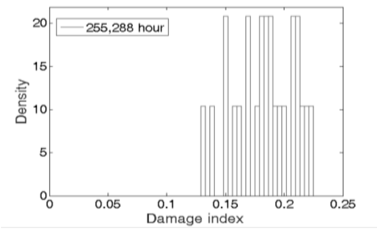


(j)

Figure. 4-3 Histograms based on the damage index (a) 74,327 hours, (b) 95,097 hours, (c) 115,671 hours, (d) 146,708 hours, (e) 157,995 hours, (f) 186,478 hours, (g) 201,671 hours, (h) 212,522 hours, (i) 213,175 hours, and (j) 255,288 hours

4.3 Damage Growth Model using Sporadically Measured and Heterogeneous On-site Data

This section proposes a new damage growth model that utilizes the damage indices from hardness data. Bayesian inference and MCMC techniques are used to update the parameters of the damage growth model in conjunction with the stochastic nature of the damage indices. The proposed model is applied to predict the RUL of steam turbines in a case study outlined in Chapter 4.4.

4.3.1 Proposed Damage Growth Model

Damage growth models based on hardness data are rarely studied, even though damage growth or degradation models are needed for predicting the RUL of steam turbines. In general, model parameters can be estimated using expert knowledge and experimental data. Figure 4-3 shows the histograms of the hardness-based damage index estimated from heterogeneous turbines with different operating times. The histograms provide an important observation. The damage index monotonically increases over operating time, although there is uncertainty that arises due to sporadic measurements from heterogeneous turbines. It is confirmed from observation that the hardness-based damage index can be used to represent damage growth.

A regression curve was built to understand damage growth behaviour over operating time, as shown in Figure 4-4. Ten sets of hardness data measured at

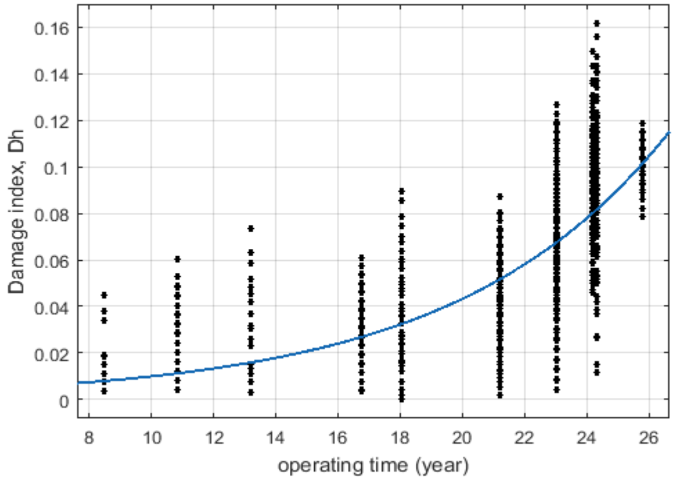


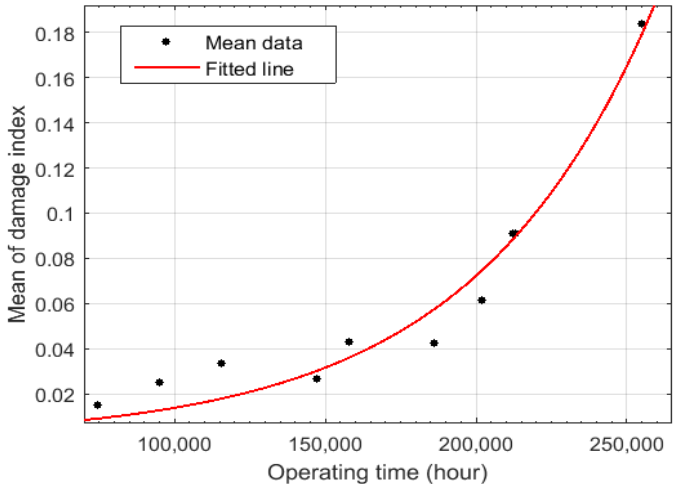
Figure 4-4 Fitted line using regression methods

different operating times were used to estimate the damage indices plotted in the figure. The regression curve demonstrates the monotonic increase of the damage index over the entire lifetime. Moreover, the variability of the damage index increases with time. It is believed that greater variability over time mainly arises from sporadic measurements and the heterogeneity of turbines in terms of manufacturers and operating conditions. This necessitates the definition of a damage growth model in a Bayesian sense. This study thus proposes a Bayesian approach to the damage growth model as a function of operating times, as shown in equation (4-3). It is assumed that the time-varying damage index follows a Gaussian distribution, of which parameters can be updated with new hardness data using Bayesian inference. This assumption may not be ideal at the beginning of operation due to its biased nature. However, the normal distribution can represent the distribution of the damage index well at later operating times. This assumption is more important than at beginning times from the viewpoint of damage prediction, because the histograms become a uni-modal and symmetric distribution at later operating times. The damage growth model can be thus defined in the form of a distribution as

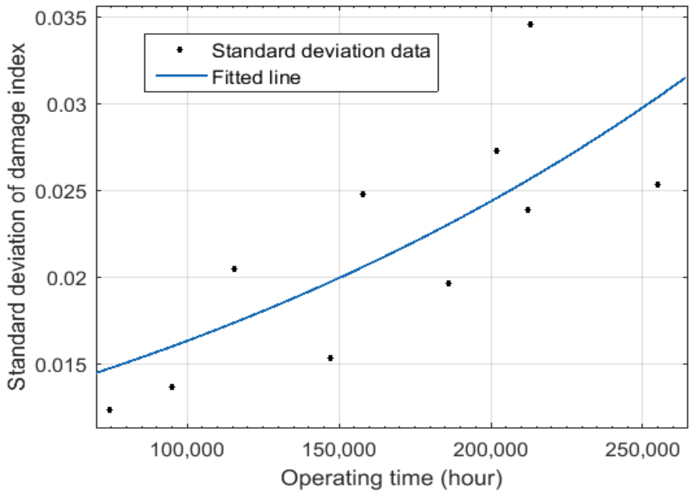
$$D(\mathrm{t}) \sim \mathrm{N}(\mu_D(t), \sigma_D(t)) \tag{4-3}$$

where the mean $\mu_D(t)$ and standard deviation $\sigma_D(t)$ of the time-varying damage exponentially increase over operating time, as shown in Figure 4-5. They are thus modelled as $\mu_D(t) = \alpha_\mu exp\beta_\mu t$ and $\sigma_D(t) = \alpha_\sigma exp\beta_\sigma t$. The parameters of the mean and standard deviation of the damage are updated through Bayesian inference to reduce the uncertainty in remaining useful life, which comes from the uncertainty in the hyper-parameters α, β for the mean and standard deviation of the damage indices.

The probability distributions of the damage index were independently developed using sporadic and heterogeneous experimental data measured at different operating (or service) times. However, it is still questionable whether hardness datasets measured from different sites at various operating times can be integrated to a single a damage growth model as a homogeneous dataset. To address the challenge, the U-pooling test is used to validate the adequacy of a



(a)



(b)

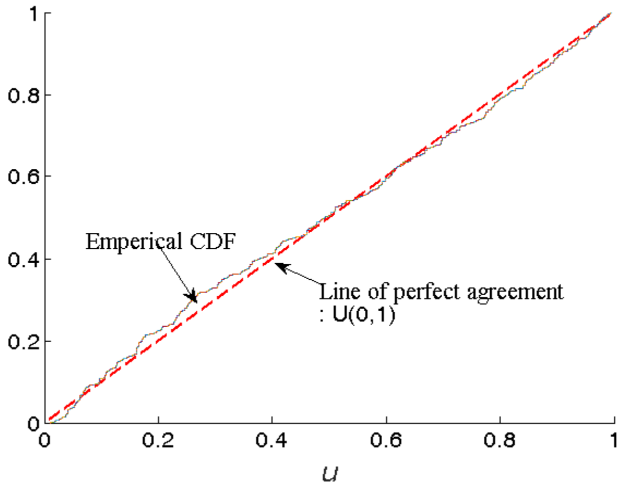
Figure 4-5 Fitted line with mean and standard deviation of the damage index distribution (a) mean and (b) standard deviation distribution model of damage indices obtained under homogeneous conditions. This is generally used to check the degree of mismatch between the dispersion of experimental data and the distribution of predicted results by calculating the area between the CDF of the uniform distribution and the empirical CDF of u_i values corresponding to the experimental data [118-122]. If valid, damage indices obtained under heterogeneous conditions can be integrated into a single metric to assess the global predictive capability of a model. In order to develop a single metric, the goodness-of-fit is first evaluated for each damage index at each data set. For each sample 'k' of damage index, u_k is the value of goodness-of-fit. Then, the area metric is calculated by integrating the difference between the CDF of uniform distribution $U(0,1)$ and the experimental CDF of u_k. Therefore, the area metric based on damage indices is defined as:

$$U_m = \int_0^1 |F_u - F_{uni}| du \tag{4-4}$$

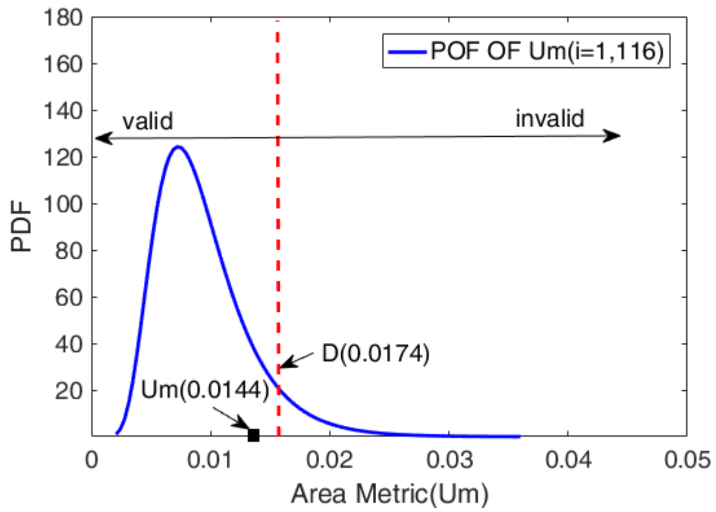
where F_u is the transformation of every damage index D_i into the CDF of responses from an assumed model; F_{uni} is the CDF of a uniform distribution $U(0,1)$.

In this research, there are ten damage indices D_i from experiments. The u_i of each damage index is calculated and the empirical CDF of each is shown in Figure 4-6 (a). Initial damage index values less than zero are physically impossible; therefore, they are excluded for data homogenization at an early stage. The calculated area after data homogenization is 0.0144; this is smaller than the threshold of 0.0175. The number of damage indices from data combination results is 1,116 and the significance level is 0.05. As a result, the null hypothesis of a normal distribution of the damage indices cannot be rejected, as shown in Figure 4-6 (b), and data homogenization enables integration of heterogeneous measured data from different turbines.

Though hardness data are obtained from heterogeneous situations, the homogeneity of the normally distributed damage index is validated and a developed damage growth model is available.



(a)



(b)

Figure 4-6 Calculation of area metric, U_m (a) area metric and (b) hypothesis testing based on the area metric with 5% confidence level

4.3.2 Bayesian Updating Scheme of the Damage Growth Model

Damage growth can be predicted by the mean and standard deviation of the damage indices. The parameters of the mean and standard deviation can be estimated by a regression technique, such as the least squares method in equation (4-3). Since typical regression methods cannot consider the statistical correlation of hyper-parameters of the damage model, the accuracy of the life prediction results is low. One of the advantages of Bayes' theorem over other parameter identification methods (e.g., the least squares method and maximum likelihood method) is its ability to identify the uncertainty structure of the identified parameters [52]. In this research, the Bayesian technique is employed to estimate the coefficients of mean, standard deviation, and statistical correlation for damage index distribution. Bayesian inference is based on Bayes' theorem:

$$p(\theta|z) = L(z|\theta)p(\theta) \tag{4-5}$$

where $L(z|\theta)$ is the likelihood of the observed data, z is conditional on the given parameters θ; $p(\theta)$ is the prior distribution of θ; and $p(\theta|z)$ is the posterior distribution of θ conditional on z. We consider posterior distributions of the coefficients of the mean and standard deviation models in the same type. The posterior distributions of the coefficients are given as:

$$p(\alpha_\mu, \beta_\mu|\mu) \propto L(\mu|\alpha_\mu, \beta_\mu)p(\alpha_\mu, \beta_\mu) \tag{4-6}$$

In the Bayesian approach, the joint posterior distribution of the hyper-parameters α, β for the mean and standard deviation of the damage indices is obtained by multiplying likelihoods $L(\mu|\alpha_\mu, \beta_\mu)$, $L(\sigma|\alpha_\sigma, \beta_\sigma)$ with prior distributions $p(\alpha_\mu, \beta_\mu)$, $p(\alpha_\sigma, \beta_\sigma)$, respectively. The likelihood is the probability of obtaining the mean and standard deviation for given hyper-parameters α, β from measured hardness data. It has been shown previously that material hardness follows a normal distribution [111]. For simplicity, it is assumed that a non-conjugate Bayes model is used for the updating process of the damage growth model. Therefore, the likelihood also follows a normal distribution, with variances s_μ^2, s_σ^2. The likelihood of the mean of the damage index can be expressed as:

$$L(\mu|\alpha_\mu, \beta_\mu) = \frac{1}{\sqrt{2\pi}s_\mu} exp\left[-\frac{1}{2}\left(\frac{\mu-\mu_D(\alpha_\mu,\beta_\mu)}{s_\mu^2}\right)^2\right] \tag{4-7}$$

where $\mu_D(\alpha_\mu, \beta_\mu)$ is an estimated mean of the damage index equation derived from equation (4-3). The standard deviation of the damage index can be modeled, similar to equation (4-7). No prior information of the hyper-parameters α, β of the mean and standard deviation is available. For practical scenario, it is difficult to obtain the prior information for the actual steam turbine's prognostics. In this researh, therefore, the prior distributions of the hyper-parameters are assumed to follow a uniform distribution whose ranges are twice larger than 90% confidence bound of the estimated hyper-parameter α, β by the Nlsq method

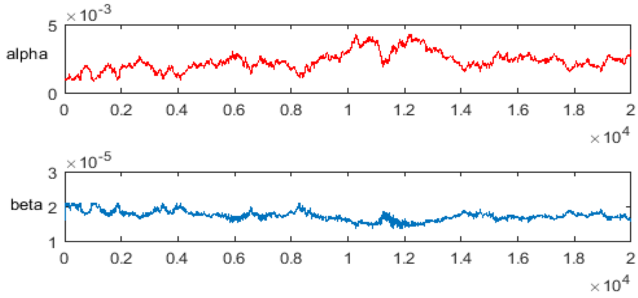
$$p\left(\alpha_{\mu,\sigma}^{0}\right) \sim U\left(\alpha_{\mu,\sigma}^{L}, \alpha_{\mu,\sigma}^{U}\right), p\left(\beta_{\mu,\sigma}^{0}\right) \sim U(\beta_{\mu,\sigma}^{L}, \beta_{\mu,\sigma}^{L}) \tag{4-8}$$

where $\alpha^{L}, \alpha^{U}, \beta^{L}, \beta^{U}$ are the lower and upper bounds of the hyper-parameters of the mean and standard deviation, respectively.

Consequently, the posterior becomes a multiplication of the likelihood and prior distributions. The prior distribution and the likelihood function, respectively, are uniform and normal distribution, as introduced here to estimate parameters of the damage growth model using Bayesian inference.

4.3.3 Damage Growth Model Updating

Since the expression of the posterior distribution of the mean and standard deviation of the damage index is available as a product of the likelihood and prior in equation (4-8), the shape of the posterior distribution can be estimated by calculating its parameters of mean and standard deviation at each time. The posterior distribution is complicated due to the correlation between multiple parameters in practical engineering applications; thus, a sampling method is effective to generate samples from an arbitrary posterior distribution. As a sampling method, Markov Chain Monte Carlo (MCMC) simulation is used to evaluate the posterior distribution after Bayesian updating [81]. MCMC simulation, in conjunction with the data augmentation technique, is computationally effective and useful to identify the correlation between hyper-parameters of the damage growth model [43, 123]. This paper uses a general Metropolis-Hastings (M-H) algorithm to generate samples that simulate the posterior distribution of two hyper-parameters α and β of the damage index. As shown in Figure 4-7, 20,000 samples for the hyper-parameters of the mean and standard deviation are generated to capture the nature of the distributions of the hyper-parameters. 4,000 samples from the initial stage are discarded for data homogenization.



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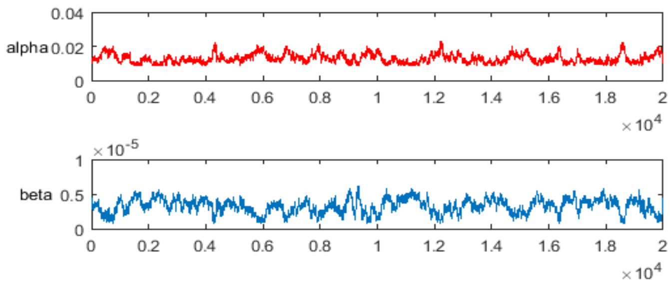
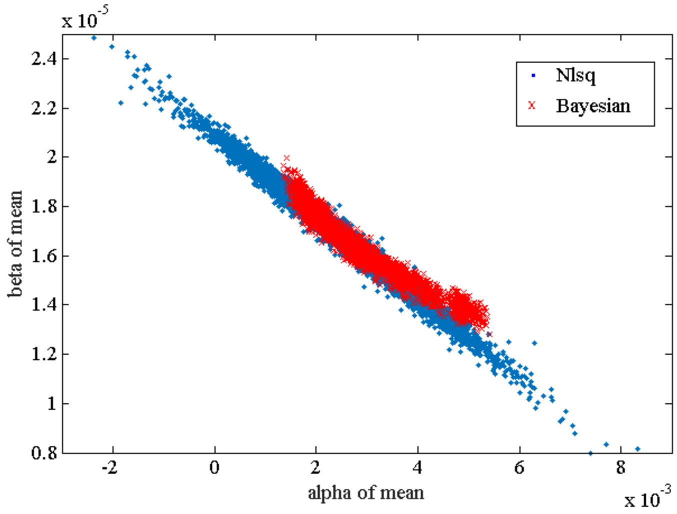


(b)

Figure 4-7 Trace iteration of a random sample (a) mean and (b) standard deviation

In general, the Nlsq method is easily used to estimate the mean and standard deviation of the damage index. Nonlinear models are more difficult to fit than linear models because hyper-parameters of the damage index cannot be estimated using regression. The Levenberg-Marquardt algorithm is used for solving the Nlsq problem [124], which estimates the distribution parameters of the damage growth model.

Figure 4-8 (a) and (b) show the joint random samples of the hyper-parameters (α and β) generated by using the Nlsq method and Bayesian method (BM). The Nlsq method yields the linear correlation of the random samples of the hyper-parameters with a constant correlation value. In contrast BM can reproduce the nonlinear correlation of the random samples. The correlation can be identified well; this is more important for accurately predicting damage growth and RUL. Table 4-3 shows the confidence intervals of the hyper-parameters of the damage growth model, along with the lower and upper bounds of the 90% intervals using both the Nlsq method and BM. Since the confidence bounds from BM are relatively narrower, the predicted mean and the standard deviation for the damage index hold less uncertainty. The probability distributions of the mean and standard deviation of the damage index can be obtained using equation (4-3) once the joint samples are obtained. To understand the effects of the correlation of the parameters in the damage growth model, the mean and standard deviation for the damage index are predicted using the Nlsq method and BM, as shown in Figure 4-9. It is observed that the second quartile



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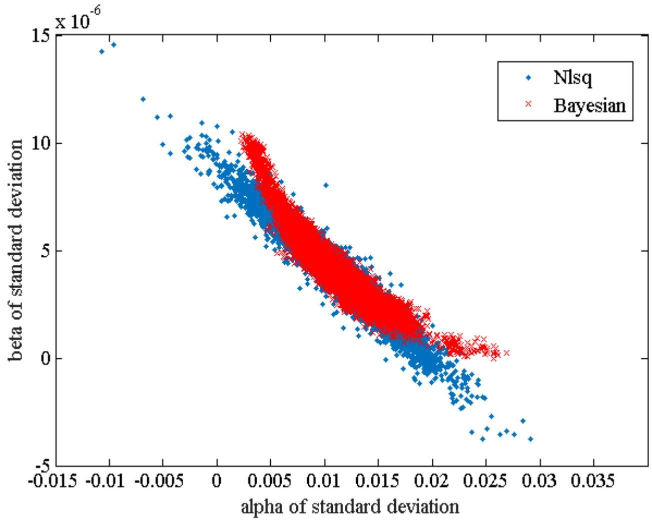


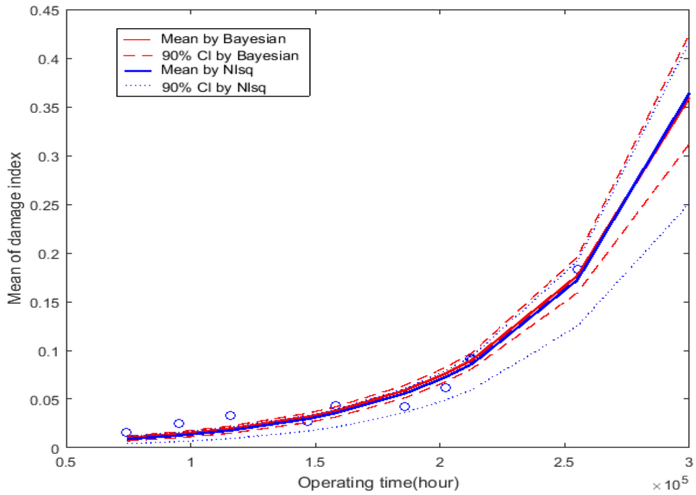
(b)

Figure 4-8 Correlated random samples of the coefficient (α,β) of the damage index (a) mean and (b) standard deviation

Table 4-3 Confidence intervals of parameters for damage growth model

Mean	α_μ				β_μ			
	5%	50%	95%	Interval	5%	50%	95%	Interval
Bayesian	0.0018	0.0031	0.0041	0.0023	1.46E-05	1.58E-05	1.80E-05	3.4E-06
Nlsq	0.0010	0.00260	0.0041	0.0031	1.406E-05	1.66Ee0-5	1.93E-05	5.2E-06

Standard deviation	α_σ				β_σ			
	5%	50%	95%	Interval	5%	50%	95%	Interval
Bayesian	0.0059	0.0106	0.0162	0.0103	2.02E-06	4.14E-06	7.02E-06	5.0E-6
Nlsq	0.0057	0.0110	0.0163	0.0106	1.50E-07	3.98E-06	6.46E-06	6.3E-6



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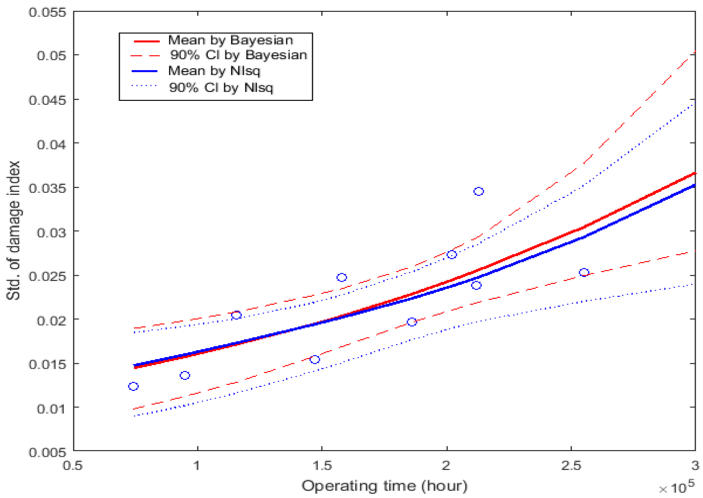


(b)

Figure 4-9 Mean and standard deviation results obtained by performing the Bayesian updating (a) mean and (b) standard deviation

(50%) of the mean and standard deviation derived from the two methods are quite similar. However, BM gives a smaller deviation of the mean and standard deviation. It is known that prediction accuracy is more sensitive to correlation than uncertainty type [125]. Each hyper-parameter is deterministically estimated and a linear correlation is added to the estimated results based on the covariance matrix in the Nlsq method. In the Bayesian method, on the other hand, the uncertainties in the unknown hyper-parameters are considered with a joint posterior distribution, and the parameters' correlation and the distribution can be identified simultaneously. As a result, it can be seen that the uncertainty of the damage growth model can be reduced by considering the nonlinear correlation of parameters for mean and standard deviation that constitute the damage growth model.

Even though measured hardness data are heterogeneous and random, a damage growth model can be constructed using the data homogenization process and Bayesian updating. Posterior distributions of the hyper-parameters (α and β) are used to predict the damage growth by using equation (4-3).

Figure 4-10 shows the results of damage growth prediction by the Bayesian and Levenberg-Marquardt method, with the 10 data sets of damage indices shown in Figure 4-3. The threshold lines of 0.2 and 0.8 are assumed and plotted as the typical ranges of the critical damage [126]. Even though both results are similar in the upper bound, differences of mean and lower bound gradually increase with time. Also, the Nlsq method clearly shows a different prediction with much wider uncertainty, even though the median is close to the true value.

These results show that the Bayesian method that uses the mean and standard deviation of the damage index is applicable for predicting damage distribution and damage growth with uncertainty. Since damage growth is predicted with all ten data sets with operating times, the results from the two methods seem to have a similar trend.

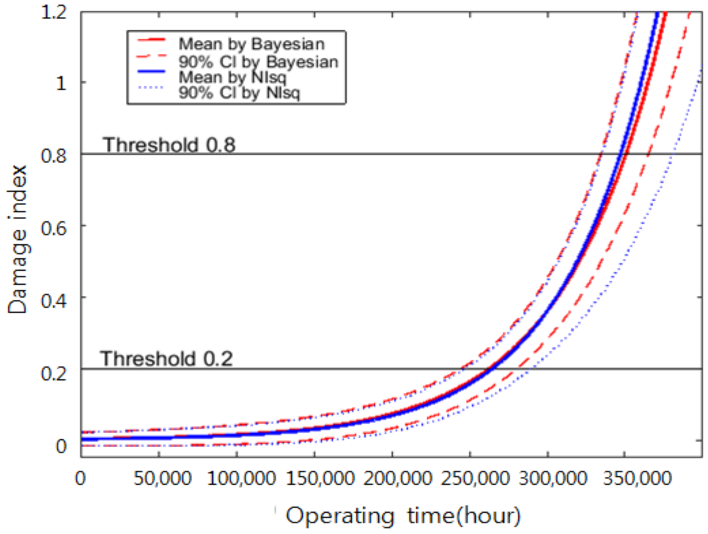


Figure 4-10 Damage growth prediction curves with all ten data

4.4 Predicting the RUL(Remaining Useful Life) of Steam Turbines

Once the parameters of the damage growth model are identified using Bayesian inference, the model can be used to predict the RUL, which is the remaining time until the damage indices grow to a threshold.

4.4.1 Damage Threshold

Typically, RUL is expressed in terms of a damage index D and an operation hour t_{op} as $t_r = (1/D - 1)t_{op}$[127]. Ideally, failure can be defined according to equation (4-2) when a damage index becomes 1. Once the hyper-parameters of the damage growth model are estimated, however, the future damage state and remaining useful life (RUL) can be predicted by progressing the damage state until the damage index reaches a threshold [128].

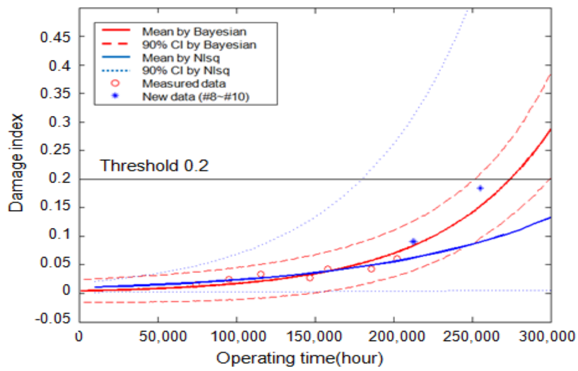
A damage threshold is of great importance to RUL prediction. However, there is to date no study about a damage threshold for steam turbines. Since a steam turbine is a rotating machine under high speed, temperature, and pressure conditions, crack initiation or fracture in elastic-plastic stress fields should be considered to be the criteria to determine the end of life. Sumio [129] proposed that the value of critical damage D_c has been ascertained to be $0.2 < D_c < 0.8$ for elastic-plastic damage.

It is well known that the average design life of a steam turbine is approximately 200,000 hours (around 25 years) [106, 130-133]. RUL prediction has been carried out to decide between life extension or retirement. Approximately 25 to 30 years is generally accepted as an acceptable usage life time. However, experience shows that a turbine can operate beyond its design life because of its designed safety margin. Table 4-1 shows two units that were retired after operating 213,175 and 255,288 hours; service life beyond the average design life. In this study, the damage index and RUL are estimated for retired turbines to determine a threshold for damage growth of a steam turbine.

For the case of damage growth prediction shown in Figure 4-11, there are large differences between Bayesian and Nlsq methods at 90% confidence intervals; this relates to the B-10 life. The B10 life metric, associated with 90% reliability, originated in the ball and roller bearing industry. This metric has become widely used in across a variety of industries. [134, 135]. The Bayesian methods predict damage growth accurately with relatively small uncertainty, compared with the Nlsq method, as shown in Figure 4-11. This study conducted RUL prediction at three operating times (0, 200,000, and 250,000 hours) to determine an appropriate failure criterion for the damage growth model. Table 4-4 shows comparison results from the damage growth model derived using Bayesian inference. By accepting the damage index, 0.2, as a failure criterion, the B50 life is 250,000 hours and B10 life is 241,000 hours. On the other hand, a failure criterion of the damage index 0.8 yields 325,000 and 335,000 hours as the B10 and B50 life, respectively. By comparing these findings with the actual retirement history of steam turbines, it is concluded that a failure criterion of the damage index 0.2 gives a reasonable RUL for a steam turbine.

Table 4-4 Comparison of RUL

Operating Time(hour)	Threshold 0.2		Threshold 0.8	
	B10	B50	B10	B50
0	240,000	250,000	325,000	335,000
200,000	40,000	50,000	125,000	135,000
250,000	-9,000	0	75,000	85,000



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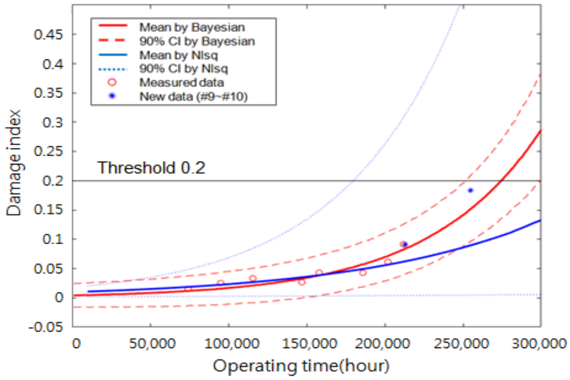

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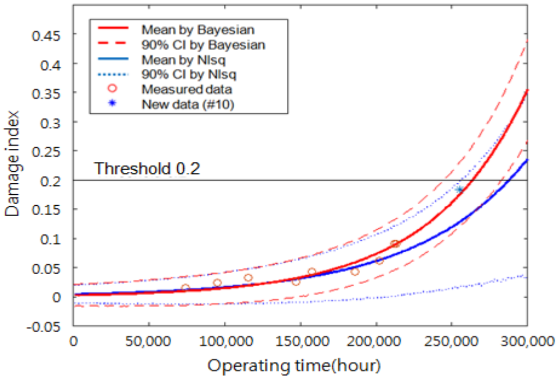


(c)

Figure 4-11 Progressive damage growth predictions with variable number of training data (a) using up to 7th damage index (b) using up to 8th damage index (c) using up to 9th damage index

4.4.2 Validation of the Proposed Damage Growth Model

Since a new damage index distribution and damage growth model, based on sporadic and heterogeneous data, is proposed, it is necessary to validate the proposed model. We used the data sets in Table 4-1 to validate the proposed Bayesian method. The prior distribution is uniform distributions as discussed in Section 4.3.2. The posterior distributions of the hyper-parameters α, β of the mean and standard deviation for the damage growth model are obtained with seven sets of ten data (i.e., A1 to E2) without 8~10th data set (i.e., F1 and H5). For the purpose of comparison, the distributions of hyper-parameters α, β are also obtained using the Nlsq method. The mean value of the last data set is used to validate the prediction. The results of damage growth prediction using the Bayesian and Nlsq methods are given in Figure 4-11(a). Next, the posterior distributions of the hyper-parameters α, β of the damage growth model are obtained with eight sets of ten data (i.e., A1 to F1) without 9~10th data set (i.e., G4 and H5). As shown in Figure 4-11(b), the 8th data point overlaps the 9th data point because their operating times and damage indices are almost identical. Compared to the actual data, the mean value calculated by the Bayesian method shows good agreement and narrow confidence bounds, whereas the damage growth prediction by the Nlsq method does poor agreement and wider confidence bounds. In Figure 4-11(c), posterior distributions of the hyper-parameters α, β are obtained with nine sets of data (i.e., A1 to G4) without the last data set (i.e., H5). As expected, the results with the proposed Bayesian method outperformed the

Nlsq method.

Although the estimation results are fairly exact in the early stages, early stages are not of interest in terms of prognostics of a steam turbine. Thus, common Nlsq methods may not be suitable to predict the damage index distribution and the RUL of a steam turbine with limited and distributed data that does not follow a normal distribution. Additionally, it is observed that uncertainty in the mean and standard deviation is reduced with more data; thus, the confidence intervals are reduced from Figure 4-10 and Figure 4-11. Figure 4-12 shows a comparison of the damage index distribution between the predicted one and the measured true one at 255,000 hours' operation. Even though the number of data in the true damage index distribution is quite small at 25, in Figure 4-12, the damage distribution from the Bayesian method is very close to the true one. Additionally, the area metrics from the Bayesian and Levenberg-Marquardt method are calculated with the aggregated 25 data. The threshold was 0.11785 for the sample size of 25 and a significance level of 0.05. The area metric result of the Bayesian method of 0.09423 is less than the threshold; whereas, the Levenberg-Marquardt result is larger than the threshold. We can also conclude that the Bayesian approach can accept the assumption of a normally distributed distribution of the damage index in the validation process.

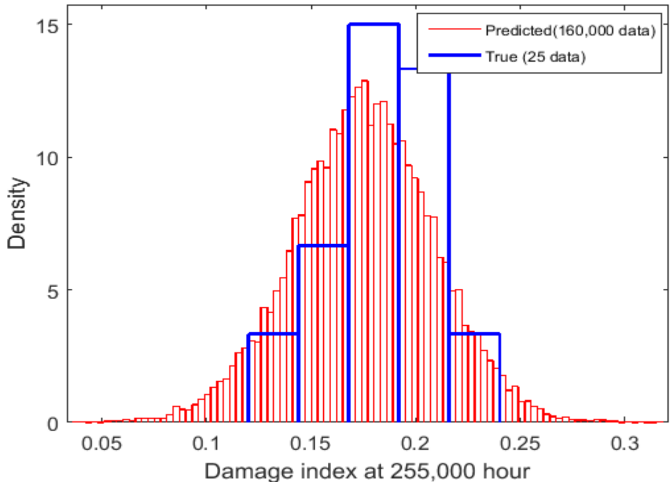
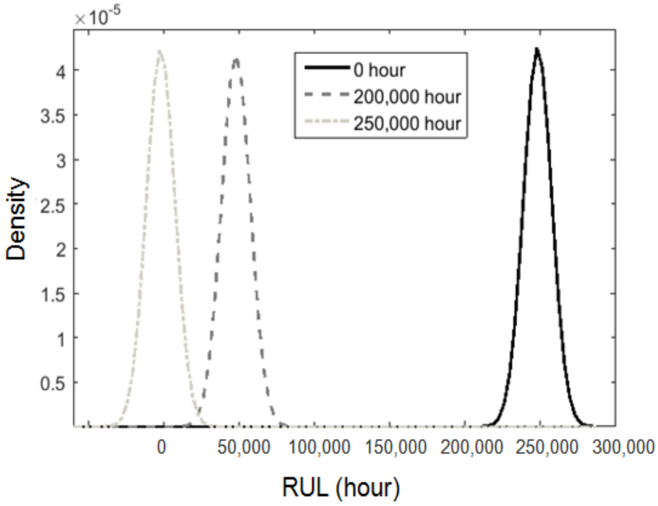


Figure 4-12 Damage index distribution at 255,000 hours operation

4.4.3 RUL Prediction

Although advanced maintenance techniques are available in the literature, they have not been well implemented in the industry for various reasons, including lack of data, lack of an efficient model, and difficulty of implementation [4]. A common practice in condition-based maintenance for turbines in power plants is to analyze the condition of the component at regular or irregular intervals; the measurement of such condition information is then used in RUL prediction. RUL predictions of steam turbines can be used to determine the maintenance schedule of whole power plants. RUL can be predicted by subtracting the PDF of the damage index from the threshold by using the mean and standard deviation distribution. Since there is no information about actual failure data of steam turbines, in this study, operating times of 0, 200,000, and 250,000 hours are used to predict RUL in the proposed damage growth model. These operating times represent the initial and average design life, respectively. PDFs and CDFs of the damage index with a 0.2 damage threshold at each operating time are shown in Figure 4-13. The change of RUL with respect to operating times is shown in Figure 4-14. In Figure 4-14, the black solid line represents the true RUL. The true RUL is a negative slope line as the RUL decreases at every operating time. The red-dashed line is the predicted RUL using the damage growth model and threshold. It was clearly shown that the confidence bound became narrow with the increase of operating times. To show the differences between thresholds, additionally, distributions of RUL at 255,000 hours are compared in Figure 4-15 and in Table 4-4. By considering the average design life and actual retirement history of steam turbines, as a result, it is concluded that a damage threshold of 0.2 yields a reasonable RUL for a steam turbine. As a result, the RUL distribution of a steam turbine can be predicted using the Bayesian method and B-lives can be determined by using the proposed damage threshold value of 0.2.



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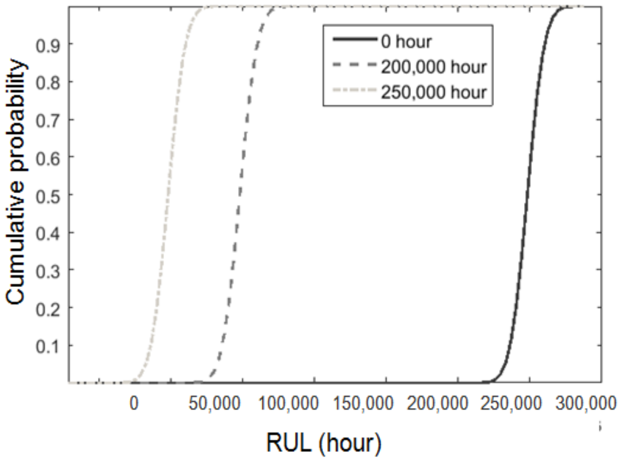


(b)

Figure 4-13 RUL distributions with different operating times under damage threshold 0.2 (a) PDF and (b) CDF

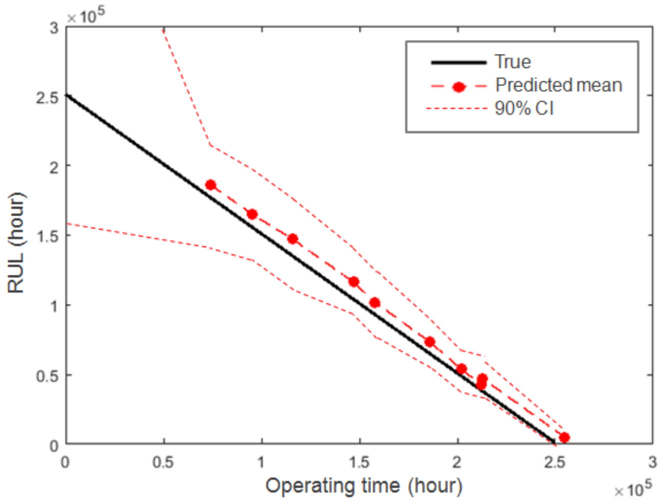


Figure 4-14 RUL prediction at each operating time

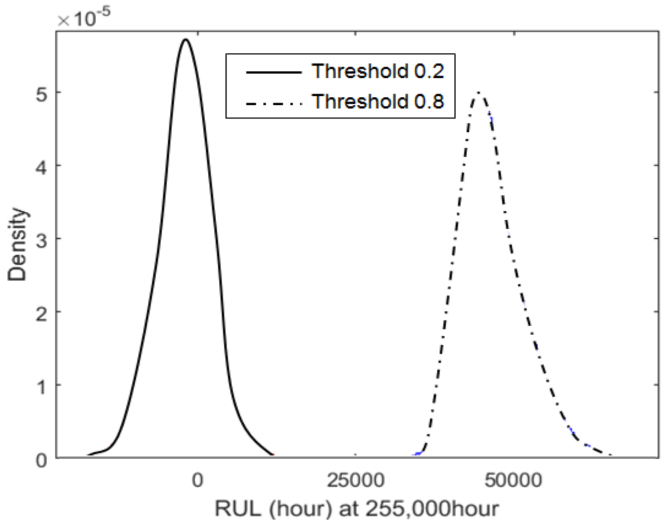


Figure 4-15 RUL distribution under damage threshold 0.2 at 255,000 hours operation

4.5 Summary and Discussion

This research presented a damage growth model and an RUL prediction methodology for aged steam turbines by using Bayesian inference. Based on the study described in this paper, several conclusions can be drawn. First, RUL prediction methodologies developed in this research incorporate the damage index into damage growth model estimation. Since the damage index, as a function of hardness, is distributed due to various uncertainties, the mean and standard deviation from the damage index distribution are used to predict the damage growth. Second, the damage growth model for a steam turbine was proposed as a function of mean and standard deviation from the damage index distribution. A Bayesian inference technique was used to estimate the probability distribution of the damage index from on-site measurements. Hardness values of the damage index were measured using a rebound hardness tester. Third, the damage growth predicted using both Bayesian and Levenberg-Marquardt methods was compared and validated. It is well known that the ability to use prior information and to choose an appropriate statistical model are advantages of Bayesian inference over the Nlsqs method, especially in cases of nonlinear correlation of unknown parameters for a damage index. Also, as more measurement data are integrated into the updating process, uncertainties in prediction can be reduced. Fourth, by comparing predictions with the actual retirement history of steam turbines, it is concluded that a damage threshold of

0.2 gives a reasonable damage distribution and RUL for a steam turbine. Through the proposed methodology, it is expected that damage states and RULs of steam turbines can be predicted using the operating time, regardless of the type of turbine.

Sections of this chapter have been published as the following journal articles:

Woosung Choi, Byeng D. Youn, Hyunseok Oh and Nam H. Kim, "A Bayesian Approach for a Damage Growth Model using Sporadically Measured and Heterogeneous On-site Data From A Steam Turbine," *Reliability Engineering & System Safety*, in Press, 2018.

Chapter 5

Mode-Dependent Damage Assessment for Steam Turbines with Creep-Fatigue Interaction Model

Since the 1980s, power generation companies have opted to build large-capacity, more-efficient units with supercritical steam conditions, which are designed for base-load operation. The typical start-up ramp rate of steam turbine recommended by the manufacture company, as there are limits to the heating rates of the rotating parts. Steam turbines require slow temperature changes to manage thermal stress to prevent thermal fatigue damage. Recently, however, new duty cycles force baseload plants to operate closer or beyond nominal design limits and through more thermal cycles than originally anticipated [136]. The life of a steam turbine is directly related to thermal transient experienced over time.

Thus the accurate knowledge of risk of the critical component, where it is susceptible to failure, is critical to the necessary to make a plan for the effective operation and maintenance. Much concern has been paid to creep and fatigue damage behavior of various systems that operated under high temperature and frequent loading condition. At a temperature beyond 30% of the absolute melting temperature of the material, significant time-dependent creep damage is accumulated in metallic material. Creep can produce large strain deformation, stress relaxation, and crack initiation and growth [137]. Fatigue damage is caused by repeated stress beyond or below yield strength of material especially at the stress concentration configuration during operation. Localized plastic deformation occurs at stress concentrated location by fatigue. Apart from fatigue, creep damage also plays an important role in the high temperature components.

The fatigue damage added to an older baseload power plant causes creep and fatigue interaction damage, rapid increase in steam turbine failures and balance-of-plant early creep fatigue failure. In effect, excessive cycling will either decrease the remaining useful life of steam turbine, or the cost to maintain the steam turbine will rise significantly. Generally, low cycle fatigue wears off seventy percent of the life of the plant facilities and creep accounts for the remaining thirty percent [138]. However, fatigue and creep damage occurs in combination though the dominant damage mechanism varies depending on the location. Their interaction is intended for conventional heat resistant steels, but their consideration in damage evaluation methods is not realized to satisfaction.

Therefore, coupling of fatigue and creep must be considered in the damage evaluation of high temperature component. Since creep and fatigue damage influences failure probability, the contribution of creep and fatigue damage in total damage is important from the point of view of risk assessment, especially failure probability [1].

In this research, the effect of operation and damage mode on the creep and fatigue damage was statistically investigated in terms of creep-fatigue damage interaction model. This Chapter is organized as follows. Section 5.1 describes provides damage mechanisms of steam turbine. Section 5.2 explains typical operation data and dominant damage model of steam turbine are summarized in Section 5.3. Total damage is statistically calculated in Section 5.4. Next, in Section 5.5, mode-dependent damage model with creep-fatigue interaction effects is investigated. This chapter also outlines the interaction effects and risk assessment considering operation and damage mode. Section 5.6 provides summary for future work.

5.1 Dominant Damage Mechanisms of Steam Turbine

A cross-sectional view of High-Intermediate Pressure (HIP) turbine rotor is shown in Figure 5-1. According to the Failure mode and Effect Analysis (FMEA) of steam turbines, HIP rotor is a key component due to its high risk. And creep and low cycle fatigue are known to be the dominant failure mechanisms of steam turbine [27, 90, 103, 107]. Figure 5-1 shows the distribution of creep and fatigue damage for HIP rotor as a typical example. The maximum creep damage portion and the maximum fatigue damage portion are located at slightly different portions. As shown in Figure 5-1, creep dominant damage portions are bore, while fatigue dominant damage portions are wheel root surface. At the bore, creep damage is dominant under load controlled stress by centrifugal force. This portion is creep dominant creep-fatigue portion. In case of fatigue dominant creep-fatigue portion, fatigue damage is dominant at wheel root surface under frequent start-ups and shutdowns by thermal fatigue [102]. Generally, when designing a steam turbine, only steady state operation is considered without cyclic load by the temperature fluctuation [139]. However, power plants have been force to operate their units in a more cyclic mode although it is designed for base-load operation mode. Cyclic stress and strain due to the cyclic and transient operation cause the additional fatigue damage. As a result, combined damage of creep and fatigue, caused by steady and transient operation such as start-up and shut-down, can significantly lead to premature failure ahead of the original design life.

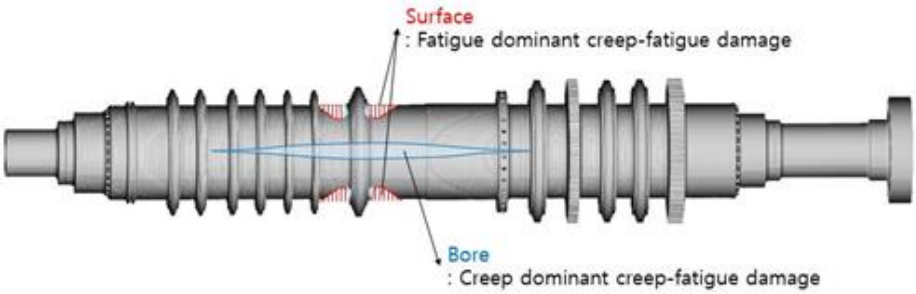


Figure 5-1 Damage mechanisms of steam turbine (HIP rotor)

5.2 Typical Operation Data of Steam Turbine

In this research, the rotor of a 500MW and 200MW supercritical steam turbine was selected for study. Typical in-service loading condition from the power plant RTDB(Real Time DB) system was adopted, shown in Figure 5-2. In the start-up procedure, large temperature gradients occur and thermal stresses usually concentrate in the key region such as high pressure stage as Figure 5-1. During start-up, the rate of increase of the main steam temperature is used to calculate fatigue damage. And the average temperature during steady state operation is used to calculate creep damage. Start-ups are generally classified according to the time the unit has spent off line. Thus an overnight shut-down is followed by a ‘hot’ start, a weekend shut-down by a ‘warm’ start, while start-up after an extended shut-down of about week would be classified as a ‘cold’ start. During cold start regime, the initial metal temperature of the HP rotor is assumed to be lower than 100℃. Thus large difference of temperatures between the surface and bore of the turbine can be expected before a steady-state regime would be reached. In contrast, during hot start the initial metal temperature of the HP rotor is assumed to be about 400~450℃, resulting in a lesser difference of temperature, $\Delta T,$ between the surface and bore of the turbine. Assuming independency of the coefficient of thermal expansion with temperature, the strain range resulting from hot start would be lower than the strain resulting from warm and cold start. Because the maximum stress arising in components subjected to cold start would be larger than the maximum stress during warm and hot start, the repetition of cold start-ups considerations are thus to be taking into account in the load change of a 500 and 200 MW steam turbine. This start-up curve is used as input data for statistical calculations of thermo-mechanical states.

Turbine units in coal power plants run at the baseload continuously throughout a year, while peakload turbines in a combined cycle power plant generally run only during periods of peak demand for electricity [114]. Based on these factors, turbine units operate with different fuel sources and power outputs, as shown in Table 5-1.

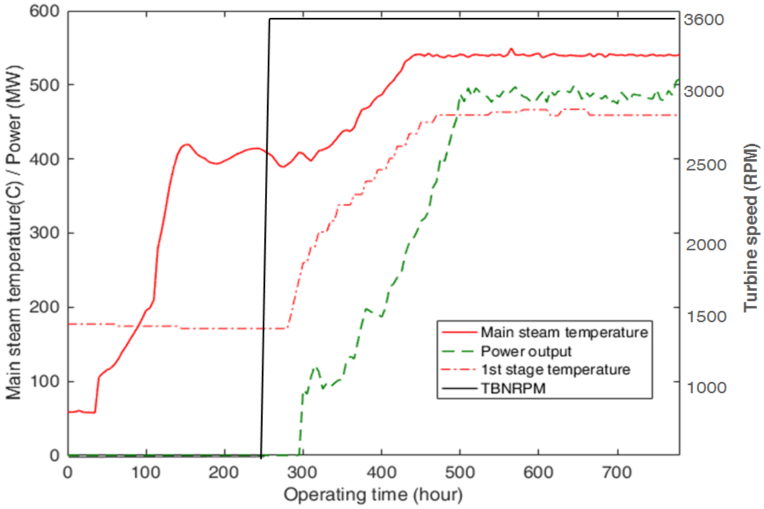


Figure 5-2 Typical cold start-up operating data

Table 5-1 Operating history

Plant/Unit	B1	B2	B3	B4	P1	P2
Output (MW)	500	500	500	500	182	200
Operation mode	Base				Peak	
Type	Coal fired power plant				Combined power plant	
Equivalent operating time	74,327	95,097	115,671	157,995	201,671	213,175
Operating time	73,547	93,937	113,511	155,315	190,551	201,535
Number of cycle	39	58	122	134	556	582

5.3 Damage Models of Steam Turbine

Damage models of steam turbine are determined by test data. In this research, creep data under the elevated temperature and time-dependent fatigue test dataset are used to calculate damage for 1Cr1Mo1/4V rotor steel; NIMS(National Institute on Materials Science, Japan) [140, 141]. The chemical compositions are summarized in Table 5-2. It is well known that a laboratory specimen of 1Cr1Mo1/4V at 565℃ is a good example of the development of creep-fatigue damage [142].

Table 5-2 Chemical composition

Composition	Cr	Mo	V	C	Si	Mn	S	Ni
wt %	1.29	1.24	0.25	0.29	0.01	0.74	0.004	0.06
others : P 0.007, Sn 0.0047								

5.3.1 Creep Damage Model

In case of 1Cr1Mo1/4V rotor steel, the coarsening of carbides and the annihilation and rearrangement of dislocation tend to occur and result in softening by long-term high temperature operation. The most commonly used creep damage (rupture) models is the Larson-Miller parameter as below [72]

$$P = T(C + \log t_r) \tag{5-1}$$

where T is the temperature and t_r is the failure time. The Larson-Miller Parameter is used to estimate the creep failure time at a given temperature and given stress level. For 1Cr1Mo1/4V rotor steels, a plot of stress and Larson-Miller Parameter resulted in a single plot, within limits of scatter, regardless of the time-temperature combination employed to derive the parameter as shown in Figure 5-3. As the log stress vs P relationship is normally a convex nonlinear curve, a multiple regression method is often used which is expressed as:

$$\mathrm{P} \cong A_1 + A_2 log\sigma + A_3(log\sigma)^2 + A_4(log\sigma)^3 \tag{5-2}$$

where A_1=11.483, A_2=–24.204, A_3=–21.394, A_4=–6.895 for 1Cr1Mo1/4V rotor steel. Then the creep failure time t_r at a different temperature and the same stress value may be estimated from equation (5-2) and (5-3) as

$$t_r = 10^{\frac{P(\sigma)}{T}-20} \tag{5-3}$$

where $P(\sigma)$ is Larson-Miller Parameter as a function of stress.

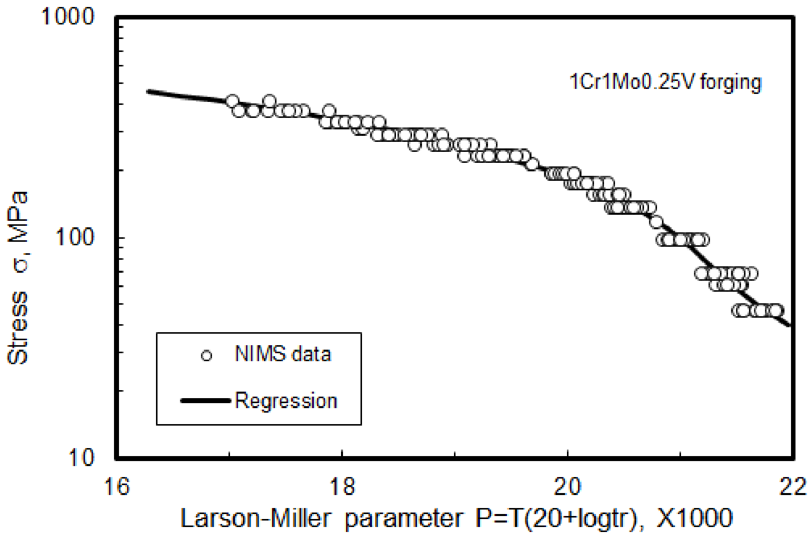


Figure 5-3 Creep rupture test data of 1CrMo1/4V rotor steel

If creep strain varies with stress, creep stress is calculated using creep strain relation and tensile strength relation at room temperature. And creep life is obtained from creep stress result. Creep analysis results are used in creep life assessment without creep stress calculation step for the purpose of conservative evaluation. Because creep strain is a temperature related value and Larson-Miller Parameter considers temperature. Creep damage is obtained using the operating time to the present time after calculating creep rupture time.

After calculating creep life t, damage rate D_c by creep damage is obtained using the operating time t_{op} below:

$$D_c = {}^{t_{op}}/_{t} \tag{5-4}$$

5.3.2 Low Cycle Fatigue Damage Model

As one of the main causes of fatigue damage in metals, the plastic strain is commonly used for crack initiation assessment [143, 144]. Curves of strain amplitude and cyclic life obtained in low cycle fatigue tests can be separated into elastic and plastic components of the strain range as shown in Figure 5-4. The prediction relationship proposed by Coffin and Manson is expressed as following:

$$\varepsilon = \varepsilon_e + \varepsilon_p = C_1 N^{\alpha} + C_2 N^{\beta} \tag{5-5}$$

where ε is total strain, ε_e is elastic strain, and ε_p is plastic strain. In equation (5-4), C_1=0.62994, C_2=22, α=-0.04572, $\beta = -0.59$ for 1Cr1Mo1/4V rotor steel. In Figure 5-4, the fatigue lives with temperature are observed to be reduced as the temperature increases.

After calculating low cycle fatigue life N_t, damage rate D_f by low cycle fatigue is obtained using the number of cycle N below;

$$D_f = {}^{N}/_{N_t} \tag{5-6}$$

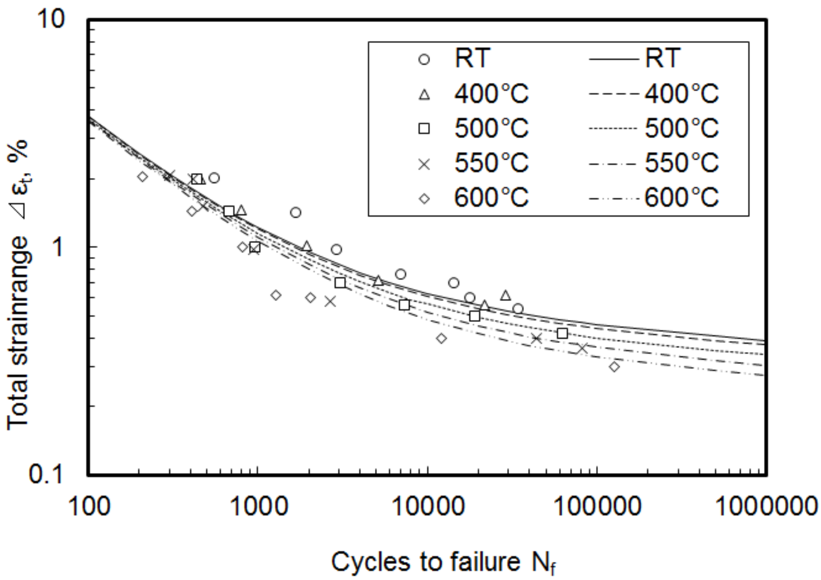


Figure 5-4 Low cycle fatigue test data of 1CrMo1/4V rotor steel

In case of creep, steady state stress is used, but low cycle fatigue life is determined by using transient thermal stress. Thus it is necessary to consider each start-up mode classified with cold, warm, hot start up for the calculation of low cycle fatigue life consumption. The individual stresses are calculated according to the start-up mode and each actual strain and low cycle fatigue damage rate is determined. The total or cumulative fatigue damage is obtained by summation of the fatigue damage rate at each start-up conditions.

5.3.3 Creep-Fatigue Damage Model

Among the various methods of simultaneously considering creep and fatigue damage from the Table 2-1 in Chapter 2, Miner's linear damage accumulation method was a dominant approach to analyze the creep and fatigue damage assessment due to its simplicity. In the ASME Code N47 [145] and TRD code 508 [66], creep and fatigue damage is evaluated by a linear summation of fraction of cyclic damage and creep damage. The linear summation damage rule is given by

$$\mathrm{D} = D_{creep} + D_{fatigue} \tag{5-7}$$

where D_{creep} is a time fraction of t/t_r and $D_{fatigue}$ is a cycle fraction of N/Nt.

The damage based on linear cumulative damage rule under creep-fatigue load is generally used to predict lifetime or risk of power plant components: rotor, casing and valve etc [25, 76-80, 137]. Compared with the nonlinear accumulation method, however, Miner's method is often over evaluated and it is not applicable if different kinds of damages are partially overlapped in a section [83]. To overcome limitation of linear damage model, thus, a nonlinear continuum damage mechanics (CDM) model is proposed to assess the creep-fatigue life of steam turbine rotor [81] and fatigue interaction model by the inelastic strain energy density is developed to represent the damage accumulation under stress control mode [82].

In this research, a multiple creep-fatigue interaction model for risk assessment is used as below [87]

$$\mathrm{D} = D_{creep} + D_{fatigue} + \alpha\left[D_{creep} \cdot D_{fatigue}\right]^{\beta} \tag{5-8}$$

Where α and β are hyper-parameters used in the interaction term of the nonlinear damage model. Though equation (5-8) was proposed and some hyper-parameters were estimated for turbine by Rusin [87], actual operation condition is not considered and damage calculation is not clear under the conservative assumptions. Hyper-parameters of creep and fatigue interaction model are determined according to the operation mode in this research. The total damages, combining creep and fatigue damage, are evaluated and compared according to linear and nonlinear damage model under different operation modes, respectively in Section 5.5.

5.4 Statistical Damage Calculation for Steam Turbine

5.4.1 Statistical Characterization of Creep and Fatigue Damage data

Three candidates were considered to determine the proper distribution type of damage data: normal, log-normal, and Weibull distributions. It was found that log-normal and Weibull distribution were appropriate creep and fatigue test data for 1Cr1Mo1/4V rotor steel, based on chi-square(χ^2), Komogorov-Smirnov(K-S) and Anderson goodness-of-fit(GoF) tests shown in Table 5-3 and in Figure 5-5. The functional form of the log-normal and Weibull distributions are expressed as

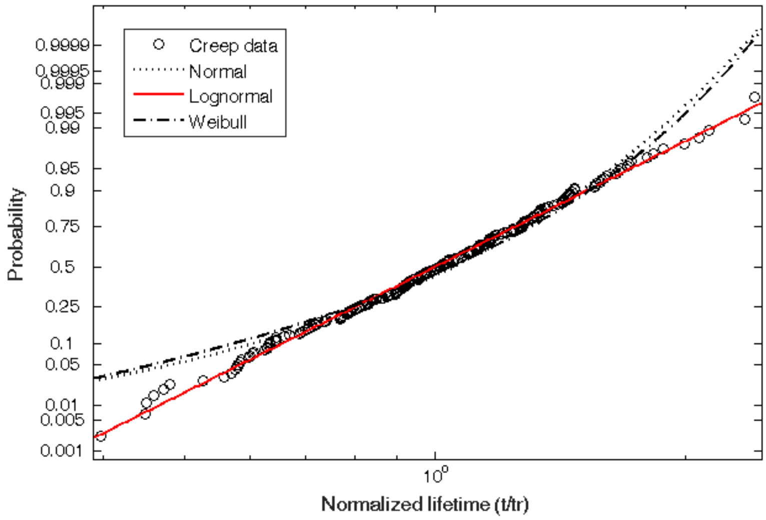
$$F = \int \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{lnN-\mu}{\sigma}\right)\right] \tag{5-9}$$

$$F = 1 - \exp[-\left(\frac{N}{\theta}\right)^{\beta}] \tag{5-10}$$

where μ, σ is mean and standard deviation of the log-normal distribution function, respectively. θ is the scale parameter, β is the shape parameter that directly affects the shape of the failure density distribution curve of the Weibull distribution function. The parameters were estimated using maximum likelihood estimator.

Table 5-3 GoF Test Results

Damage mechanism	Type	p-value		
		Chi-square GoF test	K-S GoF test	Anderson GoF test
Creep	Normal	0.13226	0.26428	0.14155
	Lognormal	**0.45084**	**0.76627**	**0.9341**
	Weibull	0.069899	0.21687	0.08093
Fatigue	Normal	0.4725	0.68708	0.6303
	Lognormal	0.20315	0.72185	0.91983
	Weibull	**0.46475**	**0.89114**	**0.94324**



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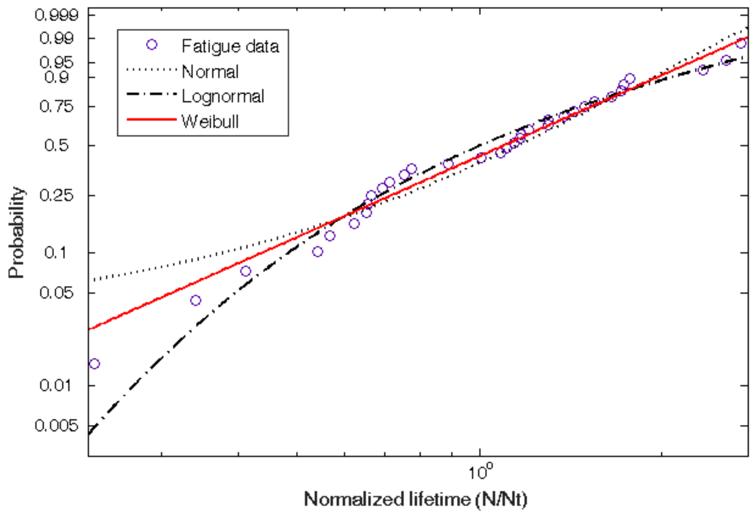


(b)

Figure 5-5 Damage distribution plot drawn on probability paper (a) creep damage and (b) fatigue damage

5.4.2 Creep Damage Calculation with Steady State Stress

Steam turbine rotor is a high-speed rotating components and stress induced by centrifugal force occurs. Radial and circumferential direction stresses must be considered simultaneously for the stress analysis. Analytic stress analysis for the hollow cylinder shows that maximum stress occurs at the surface of the cylinder. The direction of stress is the circumferential and a stress of radial direction is 0. Equation (5-11) and (5-12) are used to calculate the radial stress and circumferential stress of rotor.

$$\sigma_r = \left[\frac{(3+v)W\omega^2}{8g}\right]\left(r_i^2 + r_o^2 - r^2 - \frac{r_i^2 r_o^2}{r^2}\right) \tag{5-11}$$

$$\sigma_t = \left[\frac{(3+v)W\omega^2}{8g}\right]\left(r_i^2 + r_o^2 - \left(\frac{1+3v}{3+v}\right)r^2 - \frac{r_i^2 r_o^2}{r^2}\right) \tag{5-12}$$

By using hook's law, $\sigma_t > \sigma_r$ and maximum stress occurs at $radius = a$. This stress is a major influence on to creep; dominant damage mechanism at borehole.

$$\sigma_{bore} = \frac{W\omega^2}{4g}[(3+v)b^2 + (1-v)a^2] \tag{5-13}$$

$$\sigma_{surface} = \frac{W\omega^2}{4g}[(3+v)a^2 + (1-v)b^2] \tag{5-14}$$

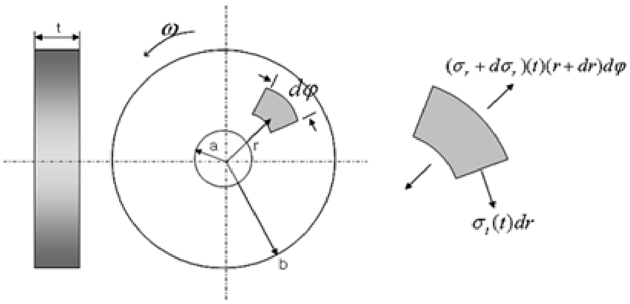


Figure 5-6 An element of cross-section of turbine rotor

From the calculated stress value from the equation (5-13) and (5-14), the creep rupture times may be calculated at a different locations such as bore or surface by using equation (5-2) and (5-3), respectively. After calculating creep rupture time t , damage rate D_c by creep damage is obtained using the operating time t_{op} from equation (5-5).

5.4.3 Fatigue Damage Calculation with Transient Strain

In addition to thermal loading induced by temperature variation, the steam turbine is subject to mechanical loadings such as steam forces and pressure, which can vary with time. Since excessive stress is not caused by pressure and the level of stress is relatively small compared to the total stress, pressure stress can be neglected [27, 146]. During start-up or shut-down, the thermal stress or strain of turbine can be calculated by finite element analysis. However, it is difficult to incorporate these complex components into the finite element code to simulate stress, strain and temperature histories. To reduce the calculation jobs, a good approximation method was proposed to assess fatigue damage of turbine rotor. The thermal strains corresponding to the transient peak-load operation mode, as well as the stress and strain concentration factors at the critical regions, need to be calculated [147]. From the approximate relationship among thermal strain, rotor geometric information and material properties, the thermal strains at the rotor surface and bore were calculated. The dimensionless nominal thermal stress C_{max} on surfaces and bore of turbine rotors can be expressed with Biot number as shown in Figure 5-7 [126, 147]

$$C_{max} = -\frac{\sigma_{max}}{E\alpha\Delta T/(1-v)} \tag{5-15}$$

where E is the elastic modulus, α is the thermal expansion coefficient, ΔT is the maximum temperature difference, and v is the poisson's ratio. σ_{max} is actual thermal stress. Having determined the nominal thermal strain for a transient condition, thermal stress concentration factor K_T and plastic strain concentration factor K_ε should be multiplied. Thermal stress concentration factor K_T can be calculated from the following formula [126, 148]

$$K_T = 1 + \sqrt{D/R}\left[\frac{DEQ}{D} - 1\right]^{1/\sqrt{2}} \tag{5-16}$$

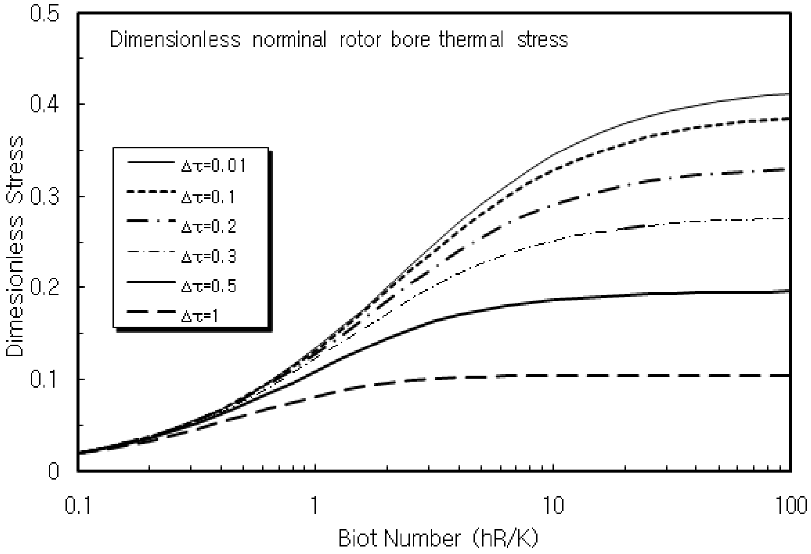
where

$$^{DEQ}/_{D} = \min\left({}^{D_d}/_{D}, {}^{D_S}/_{D} + 0.35\,{}^{L}/_{D_S}\right) \tag{5-17}$$

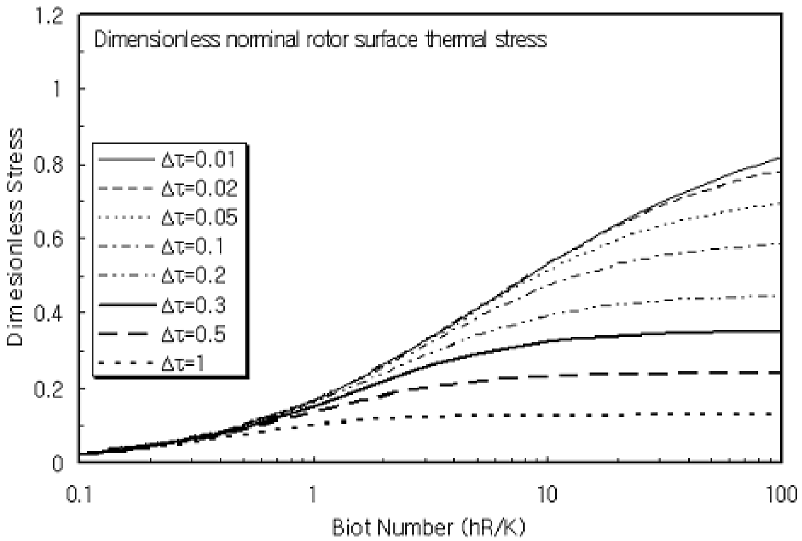
Plastic strain concentration factor K_ε for low alloy steels [149]

$$K_\varepsilon \cong K_T\left[14.958\vartheta^4 - 32.925\vartheta^3 + 26.131\vartheta^2 - 7.9607\vartheta + 1.8401\right] \tag{5-18}$$

where ϑ is normalized nominal strain range from function of total strain $\Delta\varepsilon_t$ and cyclic yield strain $2\varepsilon_y$ as $\Delta\varepsilon_t/2\varepsilon_y$. By the total strain $\Delta\varepsilon_t = K_\varepsilon \cdot C_{max}$ for a given transient, number of design cycle (creak initiation cycle) for that transient can be determined by Coffin-Manson relationship in Section 5.3.2. From the calculated design cycle from the equation (5-5), the fatigue damage may be calculated at different locations such as bore or surface by using equation (5-6), respectively.



(a)



(b)

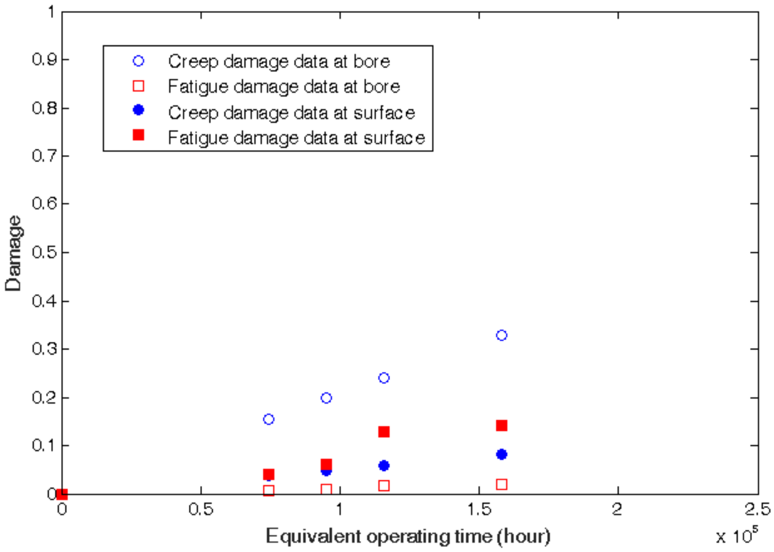
Figure 5-7 Dimensionless nominal stress (a) at bore (b) at surface

Analytical calculations are subsequently carried out next to compute the mean creep and fatigue damage evolution according to the operation and dominant damage modes shown in Figure 5-8. At the beginning of operation, there is almost no damage and the damage gradually increases with operating time.

As described for the dominant damage mechanism in Section 5.1, creep damage at bore and fatigue damage at surface are relatively larger than other calculated results by different damage mechanisms at the same location and at the same operation time.

Though creep and fatigue damage occurs at the same time, the damage result caused by creep, which is the dominant damage mechanism in the bore, is relatively large over the entire operation time. Especially, fatigue damage at the surface has similar results with creep damage at the bore in the peakload operation under cyclic loading as shown in Figure 5-8.

Each damage results according to the operation mode and the damage mode using the actual field information are used to determine the mode-dependent multiple damage interaction model for steam turbine in Section 5.5.



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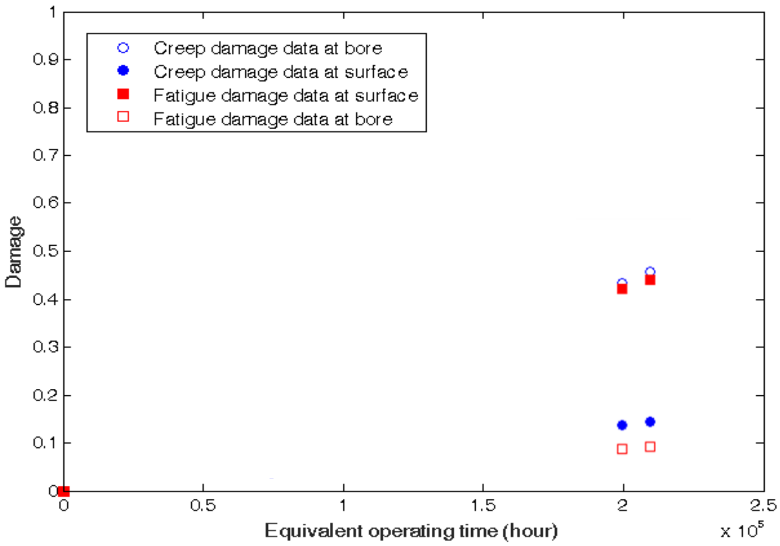


(b)

Figure 5-8 Comparison of mean damage evolution with operating time (a) baseload (b) peakload steam turbine

5.5 Mode-Dependent Multiple Damage Interaction Model

5.5.1 Estimation of damage interaction parameters

As shown in Table 5-1, in this research, the baseload and peakload are separately analyzed since the baseload turbine is in a relatively short operation time range compared to the peakload turbine. In order to investigate the behavior of creep and fatigue damage according to the operation mode, stresses and damages are evaluated on the surface and at bore where the creep and fatigue damage occurred in the individual turbine operated under the baseload and peakload.

The thrust-region reflective least square analysis was conducted to estimate the unknown damage interaction parameter. As interaction parameters, the mean values hyper-parameters of the multiple damage interaction model are indicated in Table 5-4. In order to elucidate the interaction effect of multiple damage mode, this research, we assume that the constants related to each damage mechanism are $a=1$ and $b=1$. The accuracy of the proposed model with interaction parameters are evaluated by comparing the true data with statistical distributions calculated by the damage model.

Table 5-4 Mean values of estimated interaction parameters

Operation Mode	Location	Damage Mode	Interaction parameters		
			α	β	RMS
Baseload	Surface	Fatigue	1.213	0.2787	0.9743
	Bore	Creep	2.038	0.3563	0.9943
Peakload	Surface	Fatigue	0.4306	0.2228	0.9951
	Bore	Creep	0.3115	0.0439	0.9942

5.5.2 Validation of mode-dependent model

The results from the mode-dependent multiple damage interaction model were compared with those from other models available in the literature. It should be noted that, to the best of our knowledge, no multiple damage interaction model considering operation and damage modes was developed for actual Steam turbine. Therefore, a comparison was conducted with a common linear model and nonlinear model derived from material test for turbine rotor steel at 157,995 and 213,175 hours, respectively. First, a linear damage summation model is widely used to describe creep and fatigue interaction for general high temperature steels [25, 76, 77, 137, 145]. Second, nonlinear model [87] is used for turbine materials. The model parameters of linear and nonlinear models are calculated by the nonlinear regression analysis and mean values are estimated using the two models. In case of baseload operation mode, as a representative example, the damages estimated using the two models are 0.2217 and 0.3016% at bore, respectively. The errors are 63.6% and 50.4%, respectively. In the peakload operation mode, the difference between the true value and the estimated value is relatively small compared with the baseload operation mode. Compared to the linear and nonlinear models, however, the mean values calculated by the proposed model show good agreements regardless of the operation mode and dominant damage mechanisms.

Consequently, we concluded that the multiple damage interaction model with new parameters in this research outperformed the existing models. A summary of the comparison is shown in Table 5-5 and Figure 5-9.

Table 5-5 Estimated damages depending on different damage model

Operation mode	Dominant damage mode	True D	Linear model		Nonlinear model		Proposed model	
			Est D	Error*	Est D	Error*	Est D	Error*
Baseload (coal-fired power plant)	Fatigue	0.6080	0.2217	63.6%	0.3016	50.4%	0.6218	11.8%
	Creep		0.3368	74.2%	0.3769	63.2%	0.6098	0.5%
Peakload (combined power plant)	Fatigue	0.8193	0.5886	28.2%	0.7763	5.2%	0.8209	0.2%
	Creep		0.5492	33.0%	0.6977	14.8%	0.8193	0.0%

*True D, Est D : True and Estimated damage at 157,995 and 213,175 hours respectively.
*Error : (True D – *Est D)*/True D

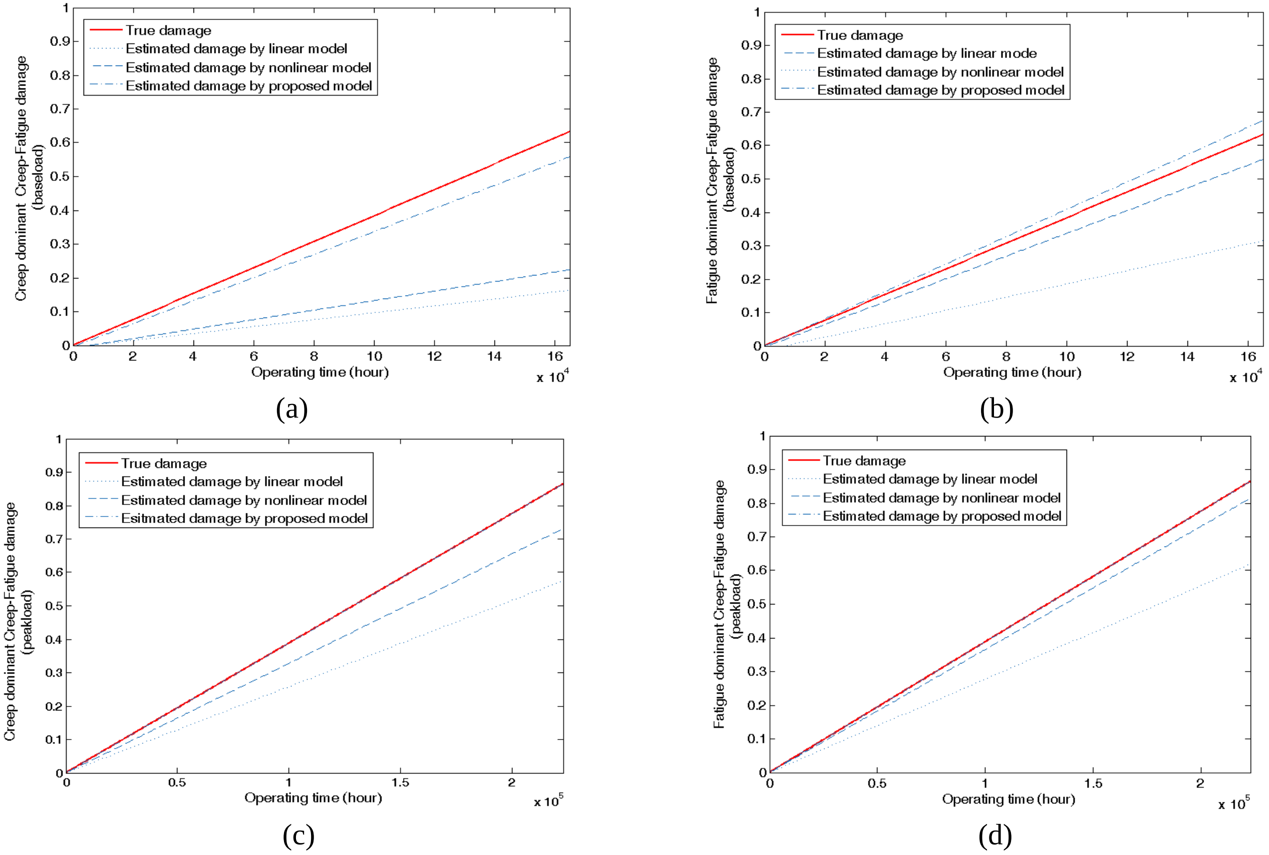


Figure 5-9 Comparison between true and estimated results considering operation modes (a) bore and (b) surface of baseload steam turbine, (c) bore and (d) surface of peakload steam turbine

5.5.3 Interaction Effects of mode-dependent damage model

The creep damage and fatigue damage fractions for all operation modes such as baseload and peakload mode depicted in the creep-fatigue interaction diagram shown in Figure 5-10. As described in Section 5.1, creep damage at the bore and fatigue damage at the surface are relatively significant considering creep and fatigue damage occurring at the same time.

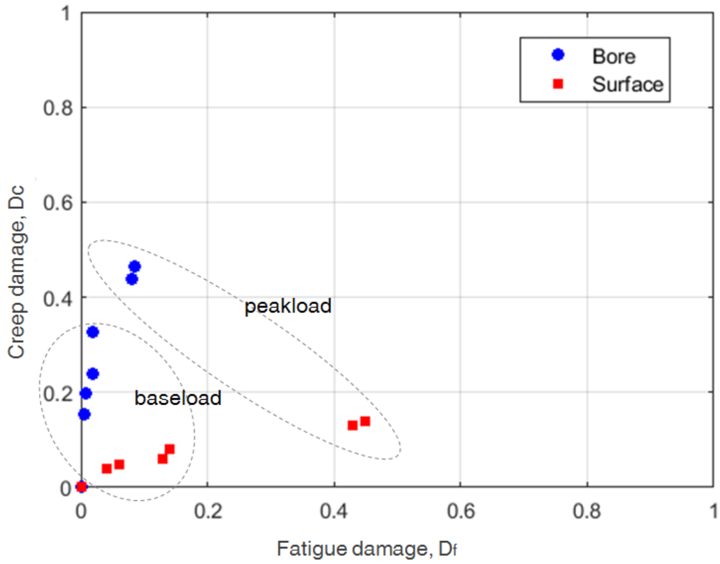
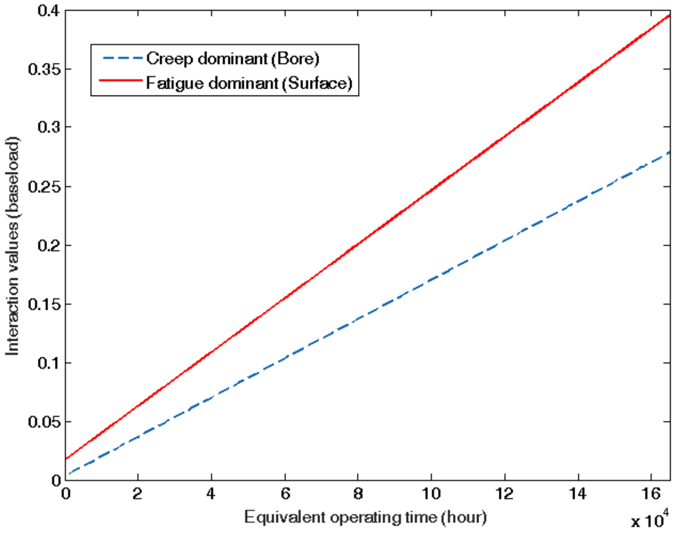


Figure 5-10 Total damage trends with operating time

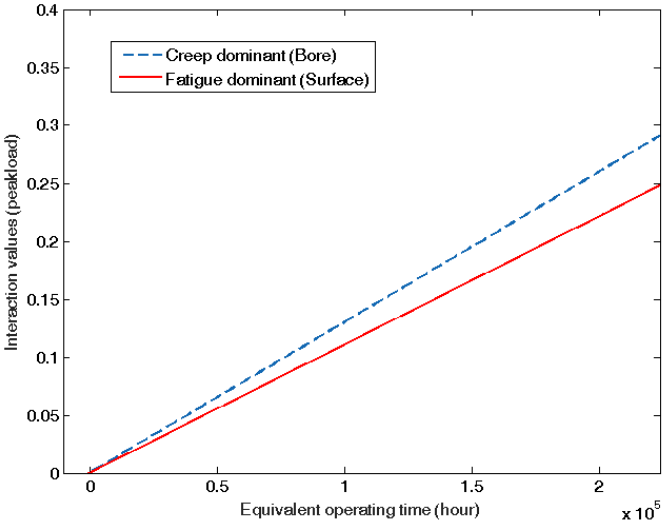
The interaction effects of the mode-dependent multiple damage model are also considered for each of the baseload and peakload steam turbine. The interaction values are calculated using the interaction term of equation (5-8) and the estimated interaction parameters in Table 5-3. In Figure 5-11, red solid line refers to the interaction value at the surface where the fatigue damage is dominant and the dotted blue lines represent the interaction value at the bore where the creep damage is significant. It is observed that the interaction value in the peakload steam turbine, affected by fatigue damage due to cyclic loading, is not relatively large. In case of baseload steam turbine, interaction value of fatigue dominant location (surface) is larger than creep dominant location (bore). It is seen from Figure 5-11 that relatively large interaction effects switch from the fatigue dominant location to creep dominant location when operation mode changes from the baseload to the peakload. Damage calculation results are re-plotted in a creep-fatigue damage summation diagram in Figure 5-12. The limiting damage summation locus shown in Figure 5-12 was established using a multiple damage interaction model. The result is due to the great deviation from the linear damage. The creep and fatigue damage interaction diagram is sensitive operation and damage modes as shown in Figure 5-12. This diagram significantly points out strong interaction effects between creep and fatigue damage.

From the results of creep-fatigue damage calculation using mode-dependent multiple damage model, two important observations can be made:

1. To calculate the damage rate or lifetime of turbine in which creep damage and fatigue damage occurs at the same time, it should reflect the interaction effects. Which is determined differently depending on the operation mode and dominant damage modes.
2. If the turbine designed for the baseload operation is operated in the peakload condition, it can be assumed that the lifetime reduction due to the interaction at the creep damage location (bore), which was relatively neglected, is accelerated.

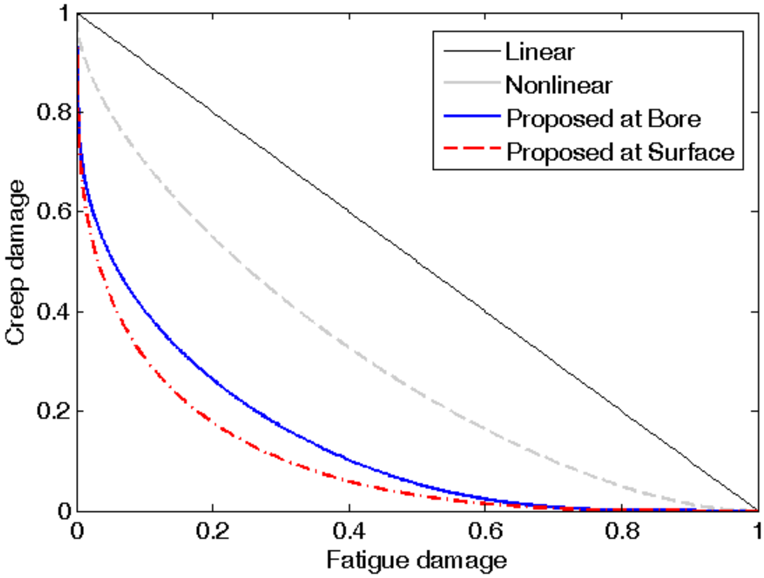


(a)

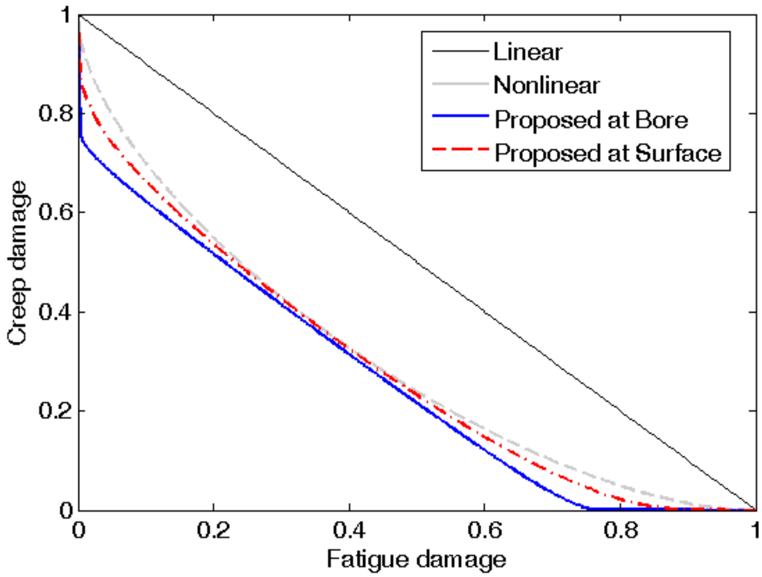


(b)

Figure 5-11 Interaction effect with operating time (a) baseload (b) peakload steam turbine



(a)



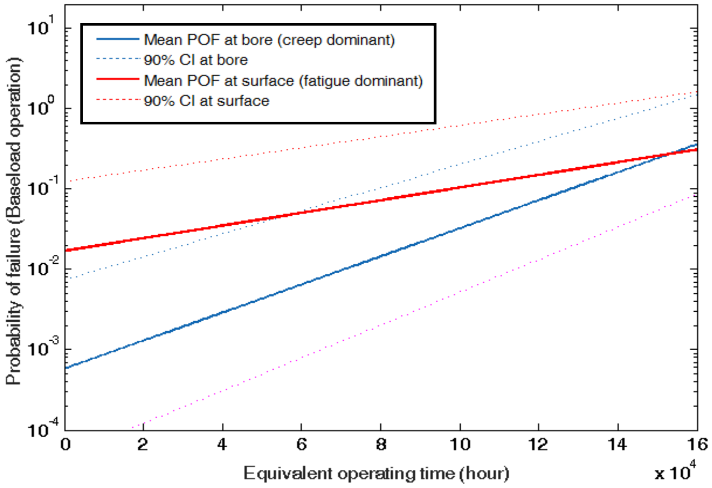
(b)

Figure 5-12 Creep-fatigue damage diagram of (a) baseload (b) peakload steam turbine

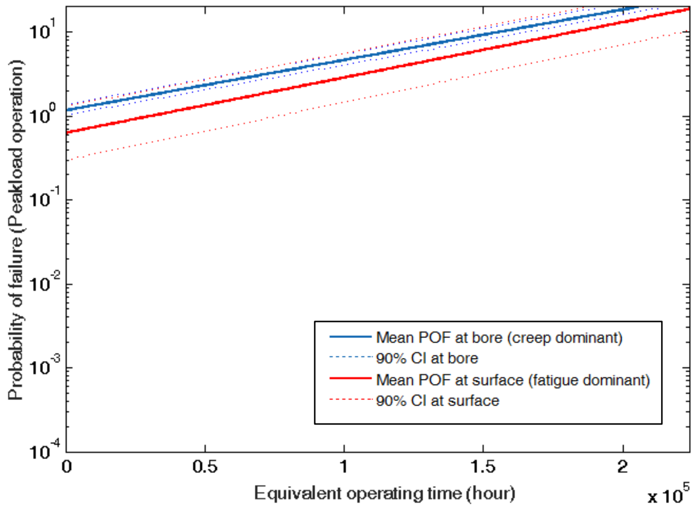
5.5.4 Case study: Risk assessment

Typical risk-based approaches reported in the literature are relatively qualitative method for developing a maintenance plan by considering the probability of the component or system for failure and likely consequences [150, 151]. Since proposed multiple damage interaction model is validated with the RUL result from empirical model-based methodologies, in this research, the technical risk is quantitatively evaluated for two types of steam turbines. This risk associated with operation modes of steam turbine as well as multiple damage interaction at failure susceptible locations is evaluated as practical case study. The risk is determined by the risk of the matrix expressed by probability of failure (POF) and consequence of failure (COF) [152]. The POF is calculated by cumulative probability of creep rupture life ratio and fatigue life ratio from the damage distribution data in Section 5.5. To understand the effect of the operation and dominant damage mode in the risk of turbine, the probability of failure is calculated as shown in Figure 5-13. It is observed that peakload operation mode gives a smaller deviation of POF even though POF is relatively large comparing with baseload.

Regardless of operation mode and dominant damage mode, as a result, the large interaction values increase the deviation of the POF considering interaction effects in Section 5.5.3. To assess the consequences of turbine failure, it is essential to fully understand the mechanism of the damage and all effects of its occurrence, the financial consequences, etc [87]. It is assumed that COF of steam turbine is a C as a consequence of failure of turbine considering actual total costs including replacement, start-up losses, profit losses in power plant company [152]. When POF and COF are determined, risk assessment results from the beginning of operation are presented in the risk matrix in Figure 5-14.



(a)



(b)

Figure 5-13 Risk assessment results with operating time: Probability of failure (a) baseload and (b) peakload steam turbine

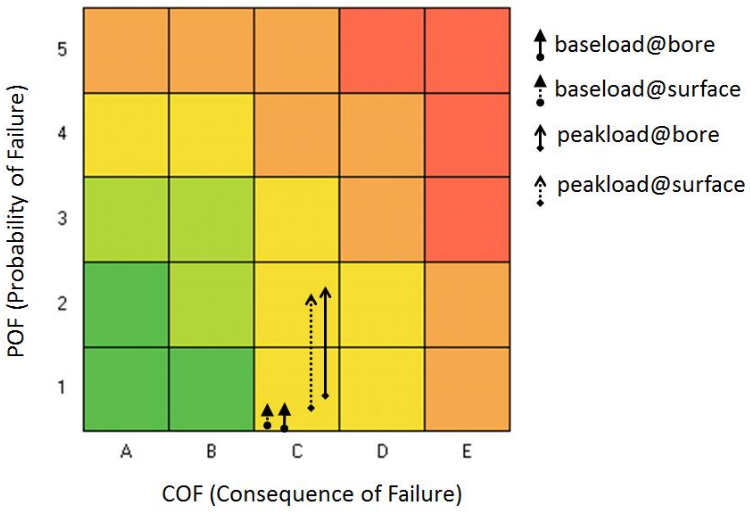


Figure 5-14 Risk matrix result by operation mode and dominant damage

5.6 Summary and Discussion

Many researches have been carried out to investigate creep and fatigue damage behavior of various systems that operated under high temperature and frequent loading condition. In case of steam turbine, as a key facility in the power plant, fatigue and creep damage occurs in combination though the dominant damage mechanism varies depending on the location. Their interaction is intended for conventional heat resistant steels, but their consideration in damage evaluation methods is not realized to satisfaction, especially for turbine steels. Also, previous studies have not fully applied the practical lifetime or risk assessment for steam turbines.

To fill this research gap, in this research, we proposed 1) a statistical approach considering multiple damage test data, 2) a novel damage interaction model, and investigate 3) mode-dependence interaction effect.

First, a statistical approach is proposed to calculate damage rate considering creep and fatigue experimental data for rotor steels, respectively. Creep damage with steady state stress and fatigue damage with transient strain are calculated using actual turbine information including geometric dimension, operation conditions.

Second, a novel multiple damage model considering the operation mode and dominant damage mode is proposed to account for the creep-fatigue interaction effects. Incorporating into the statistical analyses, the proposed model is compared with different damage models in literature and validated with the true data in Chapter 4. The creep-fatigue damage interaction model is constructed from the physical knowledge and the parameters are learned and updated using the RUL results by empirical model-based approach. Results showed a better performance compared to any of the damage summation methods.

Finally, interaction effects of creep and fatigue damage are investigated using calculated damage values. Interaction effects are depending on the operation mode and dominant damage modes. It is observed that relatively large interaction effects switch from the fatigue dominant location to creep dominant location when operation mode changes from the baseload to the peakload.

Additionally, the technical risk associated with operation modes of steam turbine as well as multiple damage interaction at failure susceptible locations is evaluated as practical case study.

In the future, the ambition is to further enhance these promising results by studying the deep learning algorithm to development health monitoring and early warning of steam turbine using all operation data relating to the steam turbine.

Sections of this chapter will be submitted as the following journal articles:

Woosung Choi, Heonjun Yoon and D. Youn, "Mode-dependent Damage Assessment for Steam Turbines with Creep-Fatigue Damage Interaction Effects," *IEEE Transaction of Industrial Electronics*, in preparation, 2018.

Chapter 6

Conclusions

6.1 Contributions and Impacts

The proposed research in this doctoral dissertation aims at development of data- and model-based RUL prediction methodologies and establishing a practical framework for steam turbine. This doctoral dissertation is composed of three research thrusts: (1) an RUL prediction framework for steam turbine with FMEA analysis; (2) a damage growth model for RUL prediction of steam turbine (empirical model-based approach); and (3) a mode-dependent damage model for steam turbine with creep-fatigue interaction (physical model-based approach). It is expected that the proposed research offers the following potential contributions and broader impacts in PHM fields.

Contribution 1: A valid framework for RUL prediction of steam turbine

The proposed framework for RUL prediction makes two technical contributions: (i) when the hardness values can be obtained in a sporadic maintenance schedule, the RUL and uncertainties can be calculated according to the empirical model-based procedure regardless of the type of turbine; (ii) if it is possible to obtain real-time operation data such as temperature and to determine a physical/empirical damage model of turbine, on-line RUL prediction is possible according to the model-based procedure. The key to success in this effort is to quantify and reduce uncertainties of predicted RUL results considering different purpose such as off-line and/or on-line prediction.

Contribution 2: A damage growth model and an RUL prediction methodology for steam turbines using Bayesian inference

This research proposes a damage growth model and an RUL prediction methodology for aged steam turbines by using Bayesian inference. The proposed method consists of three technical contributions: (i) RUL prediction methodologies incorporate the damage index into damage growth model estimation, (ii) the damage growth model for a steam turbine was proposed as a function of mean and standard deviation from the damage index distribution. A Bayesian inference technique was used to estimate the probability distribution of the damage index from on-site measurements, and (iii) using Bayesian inference, nonlinear correlation of unknown parameters for a damage index is investigated and uncertainties in prediction are reduced comparing with nonlinear least square method.

Contribution 3: Determination of damage threshold for RUL prediction of steam turbine

This research proposes a damage threshold for RUL prediction of steam turbine. The RUL, which is the remaining time until the degradation grows to damage threshold, can be predicted. Since determining the threshold depends on specific application with experience, it is difficult to determine or select the suitable threshold. Though a damage threshold is of great importance to RUL prediction, there is to date no study about a damage threshold for steam turbines. To the best of our knowledge, the proposed threshold can be treated as the first attempts to predict the RUL of steam turbine.

Contribution 4: Mode-dependent damage assessment with creep-fatigue interaction model

Many researches have been carried out to investigate creep and fatigue damage behavior of various systems that operated under high temperature and frequent loading condition. Their interaction is intended for conventional heat resistant steels, but their consideration in damage evaluation methods is not realized to satisfaction, especially for turbine steels. In this research, a novel multiple damage model considering the operation mode and dominant damage mode is proposed to account for the creep-fatigue interaction effects. Incorporating into the statistical analyses, the proposed model is compared with different damage models in literature and validated with the true data. The creep-fatigue damage interaction model is constructed from the physical knowledge and the parameters are learned and updated using the RUL results by the empirical model-based approach. Results showed a better performance compared to any of the damage summation methods.

Contribution 5: Creep and fatigue interaction effect of mode-dependent damage model

From the results of creep and fatigue damage calculation using mode-dependent damage model, the creep damage and fatigue damage fractions for all operation modes such as baseload and peakload depicted in the creep-fatigue interaction diagram. In this research, important observations can be made: (i) to calculate the damage rate or lifetime of turbine in which creep damage and fatigue damage occur at the same time, the interaction effects should be reflected. Which is determined differently depending on the operation mode and dominant damage modes. (ii) if the turbine, designed for the baseload operation, is operated in the peakload condition, it can be assumed that the lifetime reduction due to the interaction at the creep damage location (bore), which was relatively neglected, is accelerated.

6.2 Suggestions for Future Research

Although the technical advances proposed in this doctoral dissertation successfully address some challenges in RUL prediction for turbine in both data-driven and model-based approaches, there are still several research topics that further investigations and developments are required to overcome existing limitations and to improve the completeness of this research. Specific suggestions for future research are listed as follows.

Suggestion 1: Development of hybrid prognostic methodologies with uncertainty management

Regardless of online or offline data, RUL prediction can be done by data-driven approaches when physical models, loading conditions are not available. However, it would be challenging to develop RUL prediction model based on few data or no data, especially for newly commissioned systems. Since many set of training data are rare in practice, it is necessary to overcome limitations by combining suitable model-based methodologies. Hybrid prognostic methodologies that combine the data-and model-based approaches results can be considered to improve the accuracy of prediction results and reduce uncertainties. On the other hand, the prediction uncertainties in RUL prediction should be quantified and managed. The representation of the uncertainty of prognostics is a difficult task because prognostics involves both subjective and objective uncertainties, and operates over the time horizon form the past, through the present, and into the future [37].

Suggestion 2: Consolidation and verification of the proposed RUL prediction framework

The proposed RUL prediction framework provides the first step guidance but substantive procedure for steam turbine in service. Though, in this research, model-based approaches are combined with data-driven approaches to estimate model parameters using RUL and damage values, further research works are still needed to consolidate and verify the proposed framework. Especially, future researches should be devoted to the following task: a proposed framework should be generalized to consider different degradation or damage mechanism. It should not be limited to turbine but should be applicable to high temperature components such as boiler tube, piping, etc.

Suggestion 3: Deep learning based RUL Prediction using online/offline data related with turbine

Existing condition monitoring and diagnosis technology for power plant provide limited information by using specific data such as temperature, pressure and vibration separately. For accurate and comprehensive analysis, therefore, it is required to develop condition monitoring and diagnosis techniques utilizing all kinds of actual data at the same time. Various types of data obtained from power plant facilities can be used to evaluate actual conditions or notify an early warning to prevent unexpected failure by using deep learning techniques such as deep belief network (DBN), convolution neural network (CNN), and recurrent neural network (RNN), etc. In addition, more accurate and reliable methodologies can be developed based on maintenance-related history data as well as monitored operational data for efficient operation and maintenance of the power plant.

References

[1] M. Banaszkiewicz, "Multilevel approach to lifetime assessment of steam turbines," *International Journal of Fatigue,* vol. 73, pp. 39-47, 2015.

[2] Helmut Pollak, E.-W. Pfitzinger, Norbert Thamm, Mark-Andre Schwarz, "Design And Materials For Modern Steam Turbines With Two Cylinder Design Up To 700 MW," 2004.

[3] L. P. Neil Wembridge, Nigel McGimpsey, Noel Hall "Thermal power station advice," 2009.

[4] D. L. Andrew K.S. Jardine, Dragan Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing,* vol. 20, pp. 1483-1510, 2006.

[5] M. F. Khanh Le Son, Anne Barros, Eric Levrat, Benoıt Iung "Remaining useful life estimation based on stochastic deterioration models : A comparative study," *Reliability Engineering and System Safety,* vol. 112, p. 11, 2013.

[6] Byeng D. Youn, Pingfeng Wang, and Chao Hu, "A generic probabilistic framework for structural health prognostics and

uncertaintymanagement," *Mechanical Systems and Signal Processing,* vol. 28, pp. 622 - 637, 2012.

[7] Pingfeng Wang, Chao Hu, Byeng D. Youn, and Wook-Ryun Lee, "Copula-Based Statistical Health Grade System against Mechanical Faults of Power Transformers," *IEEE Transactions on Power Delivery,* vol. 27, pp. 1809 - 1819, 2012.

[8] H. Mao and S. Mahadevan, "Reliability analysis of creep–fatigue failure," *International Journal of Fatigue,* vol. 22, pp. 789-797, 2000/10/01/ 2000.

[9] H. C. Furtado and I. Le May, "Metallography in life assessment of power plants," *Materials Characterization,* vol. 36, pp. 175-184, 4// 1996.

[10] M. Nurbanasari and R. Suratman, "Creep damage assessment of a 50 MW steam turbine shaft," *MATEC Web of Conferences,* vol. 34, p. 05002, 2015.

[11] K. Saito, A. Sakuma, and M. Fukuda, "Recent life assessment technology for existing steam turbines," *JSME International journal series B,* pp. 1 - 6, 2006.

[12] "Metallographic assessment of the temperature history and remanent life of power plant components," NORDTEST2001 2001.

[13] G. Sposito, C. Ward, P. Cawley, P. B. Nagy, and C. Scruby, "A review of non-destructive techniques for the detection of creep damage in power

plant steels," *NDT & E International,* vol. 43, pp. 555-567, 10// 2010.

[14] I. A. Shibli, S. R. Holdsworth, G. Merckling, and E. C. C. Committee, *Creep and Fracture in High Temperature Components: Design and Life Assessment Issues*: DEStech Publications, 2005.

[15] J. Salonen, P. Auerkari, O. Lehtinen, and M. Pihkakoski, "Experience on in-service damage in power plant components," *Engineering Failure Analysis,* vol. 14, pp. 970-977, 9, 2007.

[16] M. Mazaheri, F. Djavanroodi, and K. M. Nikbin, "Creep life assessment of an overheated 9Cr-1Mo steel tube," *International Journal of Pressure Vessels and Piping,* vol. 87, pp. 746-752, 12, 2010.

[17] S. R. Holdsworth, "Creep-fatigue properties of high temperature turbine steels," *Materials at High Temperatures,* vol. 18, pp. 261 - 265, 2001.

[18] ECCC, "Residual Life Assessment and Microstructure," ed, 2005.

[19] Y. He, J. Dong, W. Choi, J. Jung, and K. Shin, "An Improved non-destructive replication metallography method for investigation of the precipitates in Cr-Mo-V turbine steel," *Surface and Interface Analysis,* vol. 44, pp. 1411-1414, 2012.

[20] C.C. Tasan, J. P. M. Hoefnagels, and M. G. D. Geers, "A critical assessment of indentation-based ductile damage quantification," *Acta materialia,* vol. 57, pp. 4957 - 4966, 2009.

[21] K. Fujiyama, K. Kimura, M. Muramatsu, and M. Yamada, "Evaluation of

Creep Properties of Degraded Cr-Mo-V Turbine Cast Steels through Hardness Measurement and Its Application to Life Assessment," *ISIJ International*, vol. 30, pp. 869-874, 1990.

[22] K. Fujiyama, S. Nagai, Y. Akikuni, T. Fujiwara, K. Furuya, S. Matsumoto, *et al.*, "Risk-based inspection and maintenance systems for steam turbines," *International Journal of Pressure Vessels and Piping,* vol. 81, pp. 825-835, 10// 2004.

[23] S.K. Mukhopadhyay, H. Roy, and A. Roy, "Development of hardness-based model for remaining life assessment of thermally loaded components," *International Journal of Pressure Vessels and Piping*, vol. 86, pp. 246 - 251, 2009.

[24] W.C. Oliver and G. M. Pharr, "Measurement of hardness and elastic modulus by instrumented indentation: Advances in understanding and refinements to methodology," *Journal of Materials Research,* vol. 19, p. 18, 2004.

[25] D. Hu, R. Wang, and G. Hou, "Life Assessment of Turbine Components Through Experimental and Numerical Investigations," *Journal of Pressure Vessel Technology*, vol. 135, p. 024502, 2013.

[26] V. Peshko, O. Chernousenko, T. Nikulenkova, and A. Nikulenkov, "Comprehensive rotor service life study for high & intermediate pressure cylinders of high power steam turbines," *Propulsion and Power Research*, vol. 5, pp. 302-309, 2016/12/01/ 2016.

[27] Woosung Choi, Eric Fleury, Bumshin Kim and JungSeob Hyun, "Life assessment of steam turbine components based on viscoplastic analysis," *Journal of solid mechanics and materials engineering*, vol. 2, pp. 478 - 486, 2008.

[28] R. Huang, Lifeng Xi, Xinglin Li, C.R. Liu, H. Qiu, and J. Lee, "Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods," *Mech. Syst. Signal Process.*, vol. 21, pp. 193-207, 2007.

[29] A. Mosallam, K. Medjaher, and N.Zerhouni, "Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction," *J. Intell. Manuf.*, vol. 27, pp. 1037-1048, 2016.

[30] J. Luo, K. R. Pattipati, L. Qiao, and S. Chigusa, "Model-based prognostic techniques applied to a suspension system," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 38, pp. 1156-1168, 2008.

[31] F. Cadini, E. Zio, and D. Avram, "Model-based Monte Carlo state estimation for condition-based component replacement," *Reliability Engineering & System Safety*, vol. 94, pp. 752-758, 2009.

[32] M. Daigle, B. Saha, and K. Goebel, "A comparison of filter-based approaches for model-based prognostics," in *Aerospace conference, 2012 ieee*, 2012, pp. 1-10.

[33] T. Sutharssan, C. Bailey, S. Stoyanov, and Y. Rosunally, "Prognostics and reliability assessment of light emitting diode packaging," in *Electronic Packaging Technology and High Density Packaging (ICEPT-HDP), 2011 12th International Conference on*, 2011, pp. 1-7.

[34] C. Hu, B. D. Youn, P. Wang, and J. T. Yoon, "Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life," *Reliability Engineering & System Safety,* vol. 103, pp. 120-135, 2012.

[35] B. Saha, K. Goebel, S. Poll, and J. Christophersen, "Prognostics methods for battery health monitoring using a Bayesian framework," *IEEE Transactions on instrumentation and measurement,* vol. 58, pp. 291-296, 2009.

[36] Kamal Medjaher and Noureddie Zerhouni, "Framework for a Hybrid Prognostics," *Chemical Engineering Trasactions*, vol. 33, 2013.

[37] L. Liao, and. F. Köttig, "Review of Hybrid Prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction," *IEEE Transactions on Reliability*, vol. 63, pp. 17, 2014.

[38] Racha Khelif, Brigitte Chebel-Morello, Simon Malinowski, Emna Laajili, Farhat Fnaiech, and Noureddine Zerhouni, "Direct Remaining Useful Life Estimation Based on Support Vector Regression," *IEEE Transactions on Industrial Electronics,* vol. 64, pp. 2276-2285, 2017.

[39] N. Gebraeel, M. Lawley, R. Liu, and V. Parmeshwaran, "Residual life predictions from vibration-based degradation signals: A neural network approach," *IEEE Transactions on Industrial Electronics,* vol. 51, pp. 694-700, 2004.

[40] W. Zhang, Z. Bao, S. Jiang, and J. He, "An Artificial Neural Network-Based Algorithm for Evaluation of Fatigue Crack Propagation Considering Nonlinear Damage Accumulation," *Materials,* vol. 9, pp. 483, 2016.

[41] Y.Li, T.R. Kurfess, and S. Y. Liang, "Stochastic prognostics for rolling element bearings," *Mech. Syst. Signal Process.,* vol. 14, pp. 747-762, 2000.

[42] H. Q. Nathan Bolander, Neil Eklund, Ed Hindle, Taylor Rosenfeld, "Physics-based Remaining Useful Life Prediction for Aircraft Engine Bearing Prognosis," presented at the Annual Conference of the Prognostics and Health Management Society, 2009.

[43] Dawn An, Joo-ho Choi, Tony L. Schmitz, Nam H. Kim, "In situ monitoring and prediction of progressive joint wear using Bayesian statistics," *Wear,* vol. 270, pp. 11, 2011.

[44] C. S. Byington, Watson, M., Edwards, D. , Stoelting, P. , "A model-based approach to prognostics and health management for flight control actuators," in *Aerospace Conference*, 2004, pp. 3551 -3562.

[45] C. H. Oppenheimer, and K. A. Loparo, "Physically based diagnosis and prognosis of cracked rotor shafts," *Proc. AeroSense,* pp. 122-132, 2002.

[46] D. W. Kim, H. Oh, B. D. Youn, and D. Kwon, "Bivariate Lifetime Model for Organic Light-Emitting Diodes," *IEEE Transactions on Industrial Electronics,* vol. 64, pp. 2325-2334, 2017.

[47] KyungWoo Lee, KugHwan Kim, JuYoung Kim, KwangHo Kim, ByungHak Choi and Dongil Kwon, "Safety assessment based on mapping of degraded mechanical properties of materials for power plant pipeline using instrumented indentation technique," *Journal of Loss Prevention in the Process Industries,* vol. 22, pp. 868 - 872, 2009.

[48] C.S. Seok and J.M. Koo, "Evaluation of material degradation of 1Cr–1Mo–0.25V steel by non-destructive method," *Materials Science and Engineering: A,* vol. 395, pp. 141-147, vol. 3, 25, 2005.

[49] Woosung Choi, Geewook Song, Bumshin Kim and Sungho Chang, "Indentation based life assessment for boiler tubes of fossil power plants," *Procedia Engineering* vol. 10, pp. 1035 - 1040, 2011.

[50] Alexandra Coppe, R.T. Haftka, and Nam Ho Kim, "Uncertainty Identification of Dmage Growth Prameters using Health Monitoring Data and Nonlinear Regression," presented at the Annual Conference of the Prognostics and Health Management Society, 2010.

[51] X. Guan, Y. Liu, R. Jha, A. Saxena, J. Celaya, and K. Geobel, "Comparison of two probabilistic fatigue damage assessment approaches using prognostic performance metrics," *International Journal of*

Prognostics and Health Management, vol. 5, p. 11, 2011.

[52] Dawn An, Jooho Choi, Nam H. Kim and Sriram Pattabhiraman, "Fatigue life prediction based on Bayesian approach to incorporate field data into probability model," *Structural Engineering and Mechanics,* vol. 37, p. 16, 2011.

[53] J. Chiachío, M. Chiachío, A. Saxena, S. Sankararaman, G. Rus, and K. Goebel, "Bayesian model selection and parameter estimation for fatigue damage progression models in composites," *International Journal of Fatigue,* vol. 70, p. 12, 2015.

[54] M. Compare, P. Baraldi, I. Bani, E. Zio, and D. Mc Donnell, "Development of a Bayesian multi-state degradation model for up-to-date reliability estimations of working industrial components," *Reliability Engineering & System Safety,* vol. 166, pp. 25-40, 2017/10/01/ 2017.

[55] B. D. Youn. Pingfeng Wang, Zhimin Xi, Artemis Kloess, "Bayesian Reliability Analysis With Evolving, Insufficient, and Subjective Data Sets," *Journal of Mechanical Design,* vol. 131, pp. 1 - 11, 2009.

[56] H. Oh, J. Kim, H. Son, B. D. Youn, and B. C. Jung, "A systematic approach for model refinement considering blind and recognized uncertainties in engineered product development," *Structural and Multidisciplinary Optimization,* pp. 1-15, 2016.

[57] Chao Hu, Byeng D. Youn, Pingfeng Wang, and JoungTaek Yoon,

"Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life," *Reliability Engineering and System Safety,* vol. 103, pp. 120 - 135, 2012.

[58] G. Thomas, and R. Dawson, "The effect of dwell period and cycle type on high strain fatigue properties of 1Cr1Mo1V rotor forsings at 500-550^{o}C," presented at the In: Proc. Intern. Conf. on Engineering Aspects of Creep, 1980.

[59] D. A. Miller, R.H. Priest, E.G. Ellison, "A review of material response and life prediction techniques under creep fatigue loading conditions," *High Temp. Mater. Process.*, vol. 6, pp. 155-194, 1984.

[60] V. Bicego, C. Fossati, S. Ragazzoni, "Low cycle fatigue characterisation of a HP-IP steam turbine rotor," in *Low cycle fatigue*, H. O. Soloman, Ed., ed Philadelphia: ASTM STP 942, 1988.

[61] Y. Takahashi, B. Dogan, and D. Gandy, "Systematic Evaluation of Creep-Fatigue Life Prediction Methods for Various Alloys," *Journal of Pressure Vessel Technology*, vol. 135, p. 061204, 2013.

[62] F. Özkan and J. Aktaa, "Creep fatigue assessment for EUROFER components," *Fusion Engineering and Design,* 2015.

[63] E.L. Robinson, "Effect of temperature variation on the long-time rupture strength of steels," *Transactions of ASME,* vol. 75, pp. 777-780, 1952.

[64] S. Taira, *Lifetime of structures subjected to varing load and temperature*.

New York: Academic Press, 1960.

[65] Case N-47-21, "Class 1 Components in Elavated Temperature Service," in *ASME Boiler and Pressure Vessel Code*. New York, 2001.

[66] "TRD 508, Inspection and testing, with Annex 1: Additional tests on components -Methods for the calculation of components having time-dependent design strength values," 1986.

[67] S. Holdsworth, "Creep-fatigue interaction in power plant steels," *Materials at High Temperatures,* vol. 28, pp. 197 - 204, 2011.

[68] R. W. Bailey, "The Utilisation of Creep Test Data in Engineering Design," *Proceedings of the Intstitute of Mechanical Engineering,* vol. 131, pp. 131-349, 1935.

[69] M. Evans, "Predicting Times to Low Strain for 1Cr1MoV Rotor steel using a 6-θ projection Technique," *Journal of Materials Science*, vol. 35, pp. 2937-3948, 2000.

[70] A. Graham, K. F. A. Walles, "Relationships Between Long and Short Time Creep and Tensile Properties of a Commercial Alloy," *Journal of Iron steel Institute,* 1955.

[71] WooSung Choi, Eric Fluery, Gee Wook Song, Bum Shin Kim and Sung Ho Chang, "Study on Creep Damage Model of 1Cr1Mo1/4V Steel for Turbine Rotor," *KSME-A,* vol. 35, pp. 447 - 452, 2011.

[72] H. Kraus, *Creep Analysis*. New York: John Wiley & Sons Canada, 1980.

[73] T. J. Delph, D. L. Berger, D. G. Harlow, and M. Ozturk, "A Probabilistic Lifetime Prediction Technique for Piping Under Creep Conditions," *Journal of Pressure Vessel Technology,* vol. 132, p. 051206, 2010.

[74] R. P. Skelton, "High Strain Fatigue Testing at Elevated Temperature," *Trans. Indian Inst. Metals,* vol. 35, pp. 519-534, 1982.

[75] S.-P. Zhu, H.-Z. Huang, W. Peng, H.-K. Wang, and S. Mahadevan, "Probabilistic Physics of Failure-based framework for fatigue life prediction of aircraft gas turbine discs under uncertainty," *Reliability Engineering & System Safety*, vol. 146, pp. 1-12, 2, 2016.

[76] K. Yagi, O. Kanemaru, K. Kubo and C. Tanaka, "LIFE PREDICTION OF 316 STAINLESS LOADING STEEL UNDER CREEP-FATIGUE," *Fatigue Fract. Engng Marer. Struct.,* vol. 9, pp. 395-408, 1987.

[77] K. Yagi, K. Kubo, "Evaluation of creep-fatigue interaction based on creep damage mode," in *Low cycle fatigue and elasto-plastic behavior of materials,* pp. 242 - 247, 1992..

[78] A. Rusin, "Assessment of operational risk of steam turbine valves," *International Journal of Pressure Vessels and Piping,* vol. 81, pp. 373-379, 2004.

[79] A.Scholz and C. Berger, "Deformation and life assessment of high temperature materials under creep fatigue loading," *Mat.-wiss.u.Werkstofftech,* vol. 36, pp. 722-730, 2005.

[80] L. Cui and P. Wang, "Two lifetime estimation models for steam turbine components under thermomechanical creep–fatigue loading," *International Journal of Fatigue*, vol. 59, pp. 129-136, 2014.

[81] Jing JianPing, Meng Guang, SunYi, Xia SongBo, "An effective continuum damage mechanics model for creep-fatigue life assessment of a steam turbine rotor," *International Journal of Pressure Vessels and Piping*, vol. 80, pp. 389 - 396, 2003.

[82] Z.C. Fan, X.D. Chen, L. Chen, J.L. Jiang, "A CDM-based study of fatigue-creep interaction behavior," *International Journal of Pressure Vessels and Piping*, vol. 86, pp. 628-632, 2009.

[83] Y. Xiao, "A multi-mechanism damage coupling model," *International Journal of Fatigue*, vol. 26, pp. 1241-1250, 2004.

[84] C. Qi and Y. Sun, "Multi-damage life assessment under continuous damage mechanics," in *2016 Prognostics and System Health Management Conference (PHM-Chengdu)*, pp. 1-6, 2016.

[85] D.C. Shang, G.Q. Sun, C.L. Yan, J.H. Chen, and N. Cai, "Creep-fatigue Prediction under Fully-Reversed Multiaxial Loading at High Temperatures," *International Journal of Fatigue*, vol. 29, pp. 705-712, 2007.

[86] L.J. Chen, Z. G. Wang, G. Yao, and J.F. Tian, "An assessment of Three Creep-fatigue prediction methods for Nickel-Based Superally GH4049,"

Fatigue and Fracture of Engineering Materials and Structures, vol. 23, pp. 509-519, 2008.

[87] A. M. Rusin, "Technical risk involved in long-term operation of steam turbines," *Reliability Engineering and System Safety*, vol. 92, pp. 1242 - 1249, 2007.

[88] S. S. Manson and G.R. Halford, "Practical implementation of the double linear damage rule and damage curve approach for treating cumulative fatigue damage," *International Journal of Fatigue,* vol. 17, pp. 169-192, 1981.

[89] T. Goswami, "Development of generic creep–fatigue life prediction models," *Materials & Design,* vol. 25, pp. 277-288, 2004.

[90] Woosung Choi, B. D. Youn, Hyunseok Oh and Nam H. Kim, "A Bayesian approach for a damage growth model using sporadically measured and heterogeneous on-site data from a steam turbine," *Reliability Engineering & System Safety,* vol. In press, 2018.

[91] A. Aeran, S. C. Siriwardane, O. Mikkelsen, and I. Langen, "A new nonlinear fatigue damage model based only on S-N curve parameters," *International Journal of Fatigue,* vol. 103, pp. 327-341, 2017/10/01/ 2017.

[92] J. L. Chaboche and P. M. Lesne, "A non-linear continuous fatigue damage model," *Fatigue and Fracture of Engineering Materials and*

Structures, vol. 11, pp. 1-17, 1988.

[93] G. Cheng and A. Plumtree, "A fatigue damage accumulation model based on continuum damage mechanics and ductility exhaustion," *International Journal of Fatigue,* vol. 20, pp. 495-501, 1998.

[94] V. Dattoma, S. Giancane, R. Nobile, and F. W. Panella, "Fatigue life prediction under variable loading based on a new non-linear continuum damage mechanics model," *International Journal of Fatigue,* vol. 28, pp. 89-95, 2006.

[95] J. Besson, "Continuum Models of Ductile Fracture: A Review," *International Journal of Damage Mechanics,* vol. 19, pp. 3-52, 2009.

[96] S. P. Zhu and H. Z. Huang, "A generalized frequency separation–strain energy damage function model for low cycle fatigue–creep life prediction," *Fatigue & Fracture of Engineering Materials & Structures,* vol. 33, pp. 227-237, 2010.

[97] S.-P. Zhu, H.-Z. Huang, L.-P. He, Y. Liu, and Z. Wang, "A generalized energy-based fatigue–creep damage parameter for life prediction of turbine disk alloys," *Engineering Fracture Mechanics,* vol. 90, pp. 89-100, 2012.

[98] S.P. Zhu, H. Z. Huang, V. Ontiveros, L.P. He, and M. Modarres, "Probabilistic Low Cycle Fatigue Life Prediction Using an Energy-Based Damage Parameter and Accounting for Model Uncertainty,"

International Journal of Damage Mechanics, vol. 21, pp. 1128-1153, 2012.

[99] Y. Duyi and W. Zhenlin, "A new approach to low-cycle fatigue damage based on exhaustion of static toughness and dissipation of cyclic plastic strain energy during fatigue," *International Journal of Fatigue,* vol. 23, pp. 679-687, 2001.

[100] Y.J. Sun, X.Q. Liu, L.S. Hu, and X.Y. Tang, "Online life estimation for steam turbine rotor," *Journal of Loss Prevention in the Process Industries,* vol. 26, pp. 272-279, 2013.

[101] Y. Sun and L. Hu, "Low cycle fatigue life prediction of steam turbine rotor based on a new CDM model," in *Proceedings of the 33rd Chinese Control Conference*, 2014, pp. 6814-6819.

[102] M. Banaszkiewicz, "The low-cycle fatigue life prediction method for online monitoring of steam turbine rotors," *International Journal of Fatigue,* vol. In press, 2018.

[103] Y.J. Sun, Y.L. Wang, M. Li, J. Wei, "Performance assessment for life extending control of steam turbine based on polynomial methodq," *Applied Thermal Engineering*, 2016.

[104] V. S. Srinivasan, M. Valsan, K. Bhanu Sankara Rao, S. L. Mannan, and B. Raj, "Low cycle fatigue and creep–fatigue interaction behavior of 316L(N) stainless steel and life prediction by artificial neural network

approach," *International Journal of Fatigue,* vol. 25, pp. 1327-1338, 12// 2003.

[105] G. Nowak and A. Rusin, "Using the artificial neural network to control the steam turbine heating process," *Applied Thermal Engineering,* vol. 108, pp. 204-210, 2016.

[106] K. Venkatesh, P. V. Raju, and T. J. Kumar, "Residual Life Assessment of 60 MW Steam Turbine Rotor," *International Journal of Scientific and Research Publications,* vol. 2, pp. 11, 2012.

[107] K. Fujiyama, "Development of Risk-Based Maintenance Planning Program for Power Plant Steam Turbine," KEPCO Research Institute2007.

[108] D. R. Christian Spreafico, Caterina Rizzi, "A state-of-the art review of FMEA/FMECA including patents," *Computer Science Review,* vol. 25, pp. 19-28, 2017.

[109] S. Ferson, W. L. Oberkampf, and L. Ginzburg, "Model validation and predictive capability for the thermal challenge problem," *Computer Methods in Applied Mechanics and Engineering,* vol. 197, pp. 2408-2430, 2008.

[110] "Guideline on the estimation of uncertainty in hardness measurement," EURAMET, 2007.

[111] "<Equotip_Uncertainty_Clarification_Short_E_2014.01.10.pdf>."

[112] K. Kimura, K. Fujiyama, and M. Muramatsu, "Creep and fatigue life prediction based on the non-destructive assessment material degradation for steam turbine rotors," *High temperature creep-fatigue*, vol. Current japanese materials research, vol.3, pp. 247-270, 1988.

[113] N. Turtureanu. (2008) Turbine Tech: Scheduling of steam turbine inspection intervals. *Energy-Tech*.

[114] F. H. Rolf Kelhlhofer, Franz Stirnimann, Bert Rukes, *Combined-cycle gas steam turbine power plants*: PennWell, 2009.

[115] I. Park and R. V. Grandhi, "A Bayesian statistical method for quantifying model form uncertainty and two model combination methods," *Reliability Engineering & System Safety*, vol. 129, pp. 46-56, 2014/09/01/ 2014.

[116] S.P. Zhu, H.Z. Huang, R. Smith, V. Ontiveros, L.P. He, and M. Modarres, "Bayesian framework for probabilistic low cycle fatigue life prediction and uncertainty modeling of aircraft turbine disk alloys," *Probabilistic Engineering Mechanics*, vol. 34, pp. 114-122, 2013/10/01/ 2013.

[117] R. D. Jean Lemaitre, *Damage measurements*: springer, 1987.

[118] S. Ferson, W. L. Oberkampf, and L. Ginzburg, "Model validation and predictive capability for the thermal challenge problem," *Computer Methods in Applied Mechanics and Engineering*, vol. 197, pp. 2408-2430, 5/1/ 2008.

[119] S. F. William L. Oberkampf, "Model validation under both aleatory and epistemic uncertainty," National Nuclear Security Administration2007.

[120] I. B. Frenkel, A. Karagrigoriou, A. Lisnianski, A.V. Kleyner, *Applied Reliability Engineering and Risk Analysis*: Wiley, 2013.

[121] W. Li, Z. Lu, W. Chen, Z. Jiang, Y. Liu, "New Model Validation Metrics for Correlated Multiple Response," in *10th World Congress on Structural and Multidisciplinary Optimization*, Orlando, 2013.

[122] B. C. Jung, J. Park, H. Oh, J. Kim, and B. D. Youn, "A framework of model validation and virtual product qualification with limited experimental data based on statistical inference," *Struct. Multidiscip. Optim.,* vol. 51, pp. 573-583, 2015.

[123] H. Qin, W. Zhou, and S. Zhang, "Bayesian inferences of generation and growth of corrosion defects on energy pipelines based on imperfect inspection data," *Reliability Engineering & System Safety,* vol. 144, pp. 334-342, 12, 2015.

[124] H. P. Gavin, "The Levenberg-Marquardt method for nonlinear least squares curve-fitting problems," 2015.

[125] Namho Kim, Dawn An, and Jooho Choi, *Prognostics and Health Management of Engineering Systems : An introduction*: Springer, 2017.

[126] D. C. Gonyea, "Thermal stress concentration factors in large shafts," *Thermal fatigue of materialls and components, ASTM STP 612* pp. 30 -

37, 1976.

[127] Woosung Choi, Geewook Song, Bumshin Kim, Jungseob Hyun and Jaesil Heo, "Development and Application of Life-Assessment Guidelines for Fossil-Fuel Power Plant Facilities in Korea," *KSME-A*, vol. 34, pp. 1265 - 1272, 2010.

[128] Dawn An, J.H. Choi and Nam Ho Kim, "Prognostics 101 : A tutorial for particle filter-based prognostics algorithm using Matlab," *Reliability Engineering and System Safety*, vol. 115, pp. 161 - 169, 2013.

[129] S. Murakami, *Continuum Damage Mechanics*: Springer Netherlands, 2012.

[130] M. O. Speidel, J. Denk, and B. Scarlin, "Stress corrosion cracking and corrosion fatigue of steam-turbine rotor and blade materials:" Commission of the European Communities Report No EUR 13186, 65, pp. 0142-1123, 1991.

[131] V. N. Shlyannikov, Yarullin, R. R., "Method for assessment of the residual life of turbine disks," *Inorganic Materials*, vol. 46, pp. 1683-1687, 2010/12/01 2010.

[132] H. Rauschenbach, M.C.V.L. Schulz, M. Opheys, M. Siegel, "Advanced Ultrasonic application for the inspection of turbine components," presented at the 10th European Conference on Non-Destructive Testing, Moscow, 2010.

[133] A. D. Kushwaha, A. Soni, and L. Garewal, "Critical Review paper of Steam Turbine Blades Corrosion and its Solutions," *International Journal of Scientific Research Engineering & Technology,* vol. 3, pp. 9, 2014.

[134] Dongsu Ryu and S. Chang, "Novel concepts for reliability technology," *Microelectronics Reliability*, vol. 45, pp. 611–622, 2005.

[135] R. Jongen, P. Morshuis, J. Smit, and A. Janssen, and E. Gulski, "A STATISTICAL APPROACH TO PROCESSING POWER TRANSFORMER FAILURE DATA," in *19th International Conference on Electricity Distribution*, Vienna, 2007.

[136] S. Hesler. (2011) Mitigating the Effects of Flexible Operation on Coal-fired Power Plants. *Power Magazine*.

[137] H. Oh, J. H. Jung, B. C. Jeon, and B. D. Youn, "Scalable and Unsupervised Feature Engineering Using Vibration-Imaging and Deep Learning for Rotor System Diagnosis," *IEEE Transactions on Industrial Electronics,* vol. 65, pp. 3539-3549, 2018.

[138] Verformung, "Deformation and life assessment of high temperature materials under creep fatigue loading," *Mat.-wiss. u. Werkstofftech,* vol. 36, pp. 722-730, 2005.

[139] W.Z.Wang, P. Buhi, A. Klenk, and Y.Z.Liu, "The effect of in-service steam temperature transients on the damage behavior of a steam turbine

rotor," *International Journal of Fatigue*, vol. 87, pp. 471-483, 2016.

[140] NIMS. NIMS creep data sheet 9B: Data sheets on the elevated-temperature properties of 1Cr-1Mo-0.25V steel forgings for turbine rotors and shafts (ASTM A470-8) [Online].

[141] NIMS. NIMS fatigue data sheet No.58: Data sheets on elevated-temperature, time-dependent low-cycle fatigue properties of ASTM A470-8(1Cr1Mo0.25V) steel forging for turbine rotors and shafts [Online].

[142] S. Holdsworth, "Creep-Fatigue Failure Diagnosis," 2015.

[143] L.F.Coffin, "Fatigue at high temperature prediction and interpretation," *Proc Instn Mech Engrs*, vol. 188, pp. 109 - 127, 1974.

[144] S. Manson, "Behavior of Materials Under Conditions of Thermal Stress," ational Advisory Committee for Aeronautics1954.

[145] ASME, "ASME Boiler and Pressure Vessel Code," in *Case N-47-23*, ed: ASME, 1986.

[146] Woosung Choi and Jungseob Hyun, "A life assessment for steam turbine casing using inelastic analysis," *Modern Physics Letter B*, vol. 22, pp. 1141-1146, 2008.

[147] R. Viswanathan, "Life-assessment technology for fossil power plants," *Sadhana*, vol. 20, pp. 301-329, 1995/02/01 1995.

[148] D.P. Timo and G.W.Sarney, "The operation of large steam turbines to limit cyclic thermal cracking," *ASME,* pp. 1 - 12, 1968.

[149] D. C. Gonyea., "Method for low-cycle figue design including biaxial stress and notch effects," *Fatigue at elevated temperatures, ASTM STP 520,* pp. 678-687, 1973.

[150] L. Krishnasamy, F. Khan, and M. Haddara, "Development of a risk-based maintenance (RBM) strategy for a power-generation plant," *Journal of Loss Prevention in the process industries,* vol. 18, pp. 69-81, 2005.

[151] A. Hameed and F. Khan, "A framework to estimate the risk-based shutdown interval for a processing plant," *Journal of Loss Prevention in the process industries,* vol. 32, pp. 18-29, 2014.

[152] Geewook Song, B.S. Kim, Woosung Choi, Myungsoo Park, "Prediction of Maintenance Period of Equipment Through Risk Assessment of Thermal Power Plants," *Transactions of the Korean Society of Mechanical Engineering A,* vol. 37, 2013.

국문 초록

다양한 데이터 형식에 맞는 증기터빈 잔존유효수명 예측 방법론

최근 발전사간 경쟁이 치열해짐에 따라 발전 산업에서는 운전 비용을 절감하고 핵심 설비의 수명을 연장하는데 많은 노력을 기울이고 있다. 한편 운전 시간이 설계 수명에 근접함에 따라 증기터빈과 같은 핵심 설비의 열화가 가속되고 크고 작은 고장이 많이 발생하고 있다. 가속화된 열화나 예기치 못한 손상으로 발전소가 정지되면 막대한 경제적 손실과 국가적인 재해를 야기할 수 있다. 이에 따라 안정적인 설비의 운전을 가능케 하는 다양한 기술들이 개발되고 있으며 최근 들어 더욱 많은 각광을 받고 있는 시스템 건전성 관리 기술은 효과적으로 시스템의 상태를 감지, 진단, 그리고 예지하여 관리자가 유지 보수에 있어 필요한 결정을 내릴 수 있도록 도와준다. 특히 최적 유지정비 관점에서 적합한 방법론을 통해 예측된 잔존유효수명은 설비 수명에 정확한 정보를 기반으로 효과적인 유지 정비를 가능하게 한다.

증기 터빈은 발전소 수명을 결정하는 핵심 설비이기 때문에 발전소의 최적 운영을 위해 활용 가능한 정보를 최대한 활용하여 운전 중인 증기터빈의 잔존유효수명을 정확하게 예측하는 방법론의 개발이

매우 중요하다. 이에 본 박사학위 논문에서는 (1) 증기 터빈에 대한 고장모드영향분석과 연계한 잔존유효수명 예측 프레임워크, 그리고 이를 바탕으로 한 (2) 손상 성장 모델 (데이터 기반 방법론), (3) 크리프-피로 손상 상호작용을 고려한 모드 의존 손상 모델 (모델 기반 방법론) 등의 연구를 제안한다.

첫 번째 연구에서는 고장모드영향분석에 기반하여 증기터빈의 잔존유효수명을 예측하는 프레임워크를 제안한다. 프레임워크는 측정된 데이터에 기반한 방법론과 손상 모델에 기반한 방법론으로 구성된다. 오프라인이나 온라인과 같이 다른 목적으로 잔존유효수명을 예측할 때 불확실도를 평가하고 감소시킬 수 있도록 불확실도를 정량화하는 절차를 포함하였다.

두 번째 연구에서는 데이터 기반 방법론을 이용해 증기터빈의 잔존유효수명을 평가할 수 있는 손상 성장 모델의 개발을 목적으로 한다. 잔존유효수명은 손상 인자로부터 손상 성장 모델을 연계하여 예측한다. 현장에서 측정된 경도값으로부터 손상인자의 확률분포를 추정하고 손상의 성장을 평가할 때 불확실도를 고려하기 위해 베이지안 방법을 사용하였다. 제안된 손상 성장 모델을 통해 기저부하나 첨두부하에 사용되는 증기터빈의 종류에 상관없이 정확한 잔존유효수명 예측이 가능하다는 것을 검증하였다.

마지막 연구에서는 모델 기반 방법론을 이용해 크리프와 피로 상호작용이 고려된 모드 기반 손상모델을 제안하였다. 손상기구에 따른 재료 데이터를 통계적 기법으로 분석하고 실 증기터빈의 형상

정보와 운전정보를 이용해 기저부하와 첨두부하 터빈을 대상으로 크리프 및 피로 손상율을 계산하였다. 각각 계산된 손상율 결과와 크리프−피로 상호작용 모델을 통해 운전모드 또는 손상모드에 따른 증기터빈에서의 크리프와 피로 상호작용 효과를 분석하였다.

주요어: 증기 터빈
잔존 유효 수명
불확실도
베이지안 추론
크리프-피로 손상 상호작용

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