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Hybrid Prognostic Model for Residual Useful Life Estimation of Degraded Equipment

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MASTER THESIS

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Preface

This is a Master's thesis in RAMS (Reliability, Availability, Maintainability and Safety) at NTNU as part of the study program, when it was carried out during the spring semester of 2015).

In this report, The basic concepts in prognostics and health management and different diagnostic and prognostic methods have been discussed. a case study of choke valve is implemented and one hybrid model has been proposed for valve erosion.

The reader is assumed to have some basic knowledge of condition-based maintenance or prognostics and health management.

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Jie Zhang

Acknowledgment

First, I would like to thank my professor Yiliu Liu for the patient guidance of my work and the suggestions of my thesis structure.

In addition, I would like to thank Professor Anne Barros for giving guidance on Gamma process. And also I would like to thank my sister who gives me advices for modeling. Moreover, I really appreciate that Fen and Yun are often present to discuss the topics and questions what we have met in common. Finally, I would like to thank my friends for their cheering up, encouragement and support.

J.Z.

Summary and Conclusions

As the consequence of the more widely used complex systems, there has been a shift in maintenance strategy. The traditional corrective maintenance is gradually replaced by preventive maintenance or even more advanced philosophy such as condition based maintenance and prognostics and health management. This thesis introduces prognostics and health management that can implement the advanced condition-based maintenance for the more complex and dynamic systems. First, the content of prognostics and health management is discussed, and then the procedure is described as data acquisition, data processing, diagnostics and prognostics, and maintenance decision making. In addition, historical literatures about diagnostic and prognostic models are systematically and throughly reviewed. It consists of model-based models and data-driven models and the paper focuses more on data-driven models, due to its simplicity and generality. Since degradation is one of main causes for system failure either for either machinery or electronics, degradation status assessment and prognostics are discussed in this paper. Gamma process is suitable for monotonic degradation, but there is a prerequisite that the degradation indicator is observable. In order to overcome this limitation, ANNs are used to calculate the value of indicator by monitoring relevant measurable covariates. One hybrid model is proposed consists of ANNs model together with Gamma process for degradation prognostics. Bayesian estimation for updating the scale parameter of gamma process is suggested to improve the accuracy.

Chock valve is studied as a case to demonstrate how the hybrid model can be applied to estimate valve residual useful life. The case study approves the results from hybrid prognostic model, the distribution of RUL can support the maintenance decision making. This proposed hybrid model can not only be applied to subsea valves erosion prognostics, but also can be applied to other equipment degradation prognostics problem.

Contents

Chapter 1

Introduction

1.1 Background

During the past half century, more and more complex and highly embedded and automated systems has been used in industries. The cost of unavailability of these systems is so huge that no one can afford and in addition, the high reliability and availability of systems are the key to ensure the safety and environment are protected. The simplest maintenance strategy (run to failure) is out of date for the complex system. The scheduled preventive maintenance is also not economically wise to implement since it may lead to waste of components or subsystems useful life. As the maintenance cost accounts more and more of the operational cost, the need to lower the maintenance cost and at the same time without compromising safe operation is in emergency.

Condition-based maintenance has developed to minimize the unnecessary preventive maintenance by assessing actual equipments or components health condition based on real-time sensor data analysis. A lot of effort has been put on failure or fault detection and diagnostics, and the principle of diagnostics is once the monitored indicator reaches the presetting threshold, system will send alarms to inform there is something wrong within the system. Based on the diagnostic techniques, the prognostics-related techniques like fault propagation and residual useful life estimation of the system or components have only recently attracted attentions in research studies. While according to Li and Nilkitsaranont (2009), making accurate prognostic predictions allows benefits such as advanced scheduling of maintenance activities, proactive allocation of replacement parts and enhanced fleet deployment decisions based on the estimated progression of component life consumption.

In military and aerospace, Prognostics and health management (PHM) has been developed as a system that can implement the advanced condition-based maintenance strategy and focus more on prognostics and predicting the residual life. PHM has already been used in the aircraft (Carl S. Byington et al. (2004))and military for decades, and the benefits of apply PHM is apparent and remarkable. For example, the capability allows end users to improve fault isolation, better plan maintenance, reduce or eliminate inspections, and decrease time-based maintenance intervals with confidence, as well as an overall decrease in life cycle costs. Whilst in other industries PHM is still not applied widely. For example, oil and gas industry already starts to implement condition monitoring technologies to monitor the equipments' degradation, but the prognostics has not even been considered as one necessary practice. Considering the more time consuming and difficult maintenance for subsea equipments, it is imperative to apply prognostic algorithms in subsea industry to calculate the residual useful life (RUL) of the equipments, which can let the proactive maintenance practicable. Prognostics and health management is a wide topic and in this paper the main focus is the prognostic algorithms used in prognostics and health management systems.

The book George Vachtsevanos (2006) details the technologies in CBM and PHM that have been introduced by researchers and practitioners within different application domains. It contains the important concepts within this field, the data collection and processing techniques, and the diagnostics and prognostics methods. The diagnostics and prognostics methods will be reviewed in detail in Chapter 2 in this thesis.

1.2 Objectives

The main objective is to study prognostics methods that can be used in Prognostics and Health Management for predicting the residual useful life which can help the maintenance scheduling. Using a subsea choke valve as a case study to discuss how can different methods be combined together.

The sub-objectives are:

1. Summarize the prognostics and health management content and procedure;
2. Discuss different diagnostics and prognostics methods used in Prognostics and Health Management;
3. Propose a hybrid model for dealing with the equipments degradation problem;
4. Apply the hybrid model for prognostics of choke valve erosion.

1.3 Limitations

1. This thesis focus on prognostics models more than diagnostics, and it just gives a summary for different diagnostics methods. More deep understanding of diagnostics will help to understand prognostics better since prognostic models is developed based on diagnostics;
2. The report has discussed more about the machinery prognostics, the prognostics of electronics is not covered.
3. Due to time limitation and lacking of relevant knowledge, some relevant topics have not been introduced in detail, such as signal processing techniques, the system level health assessment.
4. Since no field data for the case study of choke erosion, the manually generated data is used for calculation.

1.4 Approach

The background knowledge about prognostics and health management is obtained by literature review, and in addition the most currently common used diagnostics and prognostics method are also reviewed. For choke valve erosion, Gamma process could be suitable method for erosion prognostics and residual useful life prediction, if the limitation of Gamma process can be solved. By compare the merits and limits of different models, ANNs model is chosen to solve the limitation of Gamma process together with data processing techniques.

1.5 Structure of the report

The report is structured as:

- Chapter 1 introduces the background of Prognostics and health management and objectives of this report;
- Chapter 2 gives a detailed introduction of the content of Prognostics and health management and a literature review of the relevant diagnostic and prognostic models;
- A hybrid prognostics model is proposed for the equipment degradation in Chapter 3 and the details about the ANNs model and Stochastic model are discussed;
- Chapter 4 introduces subsea choke valve as a case study, and demonstrates the hybrid prognostic model for valve erosion;
- Chapter 5 presents the summary and conclusion of the report and recommends the future works.

Chapter 2

Introduction of prognostics and health management

2.1 Evolution of maintenance technologies

The earliest maintenance techniques is basically breakdown maintenance (also called corrective maintenance or run-to-failure), where no actions are taken to maintain the equipment until it breaks and consequently needs a repair or replacement. Breakdown maintenance only applies to the equipment that is not expensive and the failure does not lead to a severe consequence. In the 1950s, preventive maintenance (planned maintenance) was introduced to prevent the catastrophic failures, which means regular inspections and maintenance is implemented in certain intervals regardless of the condition of the equipment. Bazovsky (1961) pioneers the use of mathematical optimization methods in preventive maintenance policies. Jardine (1973) introduces decision models for determining optimal replacement or overhaul interval by analyzing reliability data (e.g. historical breakdown events) and cost data. These polices do reduce some failures, but they can not eliminate all the catastrophic failures and at the same time it needs more labor or sometime is more costly. Both preventative and corrective maintenance approaches have financial implications with them. The use of conservative failure rate to decide the maintenance interval will result in components regularly being replaced away before they actually reached their end of life time. Alternatively, the use of corrective maintenance approaches makes the best use of the components serviceable time, however, the failure of components can cause damage to other part of a system, resulting in significant repair cost and down time cost. The common factor making them unsuitable is that the actual condition of the equipment is not considered.

As system and equipment become more complex and expensive, the cost of the failure of systems and corresponding cost such as down time cost and safety cost is significantly increased. In addition, high availability and reliability of the system becomes more demanding than ever. These factors drive the industries to look for a new maintenance philosophy. Eventually, condition-based maintenance(CBM) starts to play a role in different industries. CBM is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring and only when there is evidence of abnormal behaviors in the equipment. ISO (2012) defines condition monitoring (CM) as the process of monitoring a parameter of condition in machinery (vibration, temperature etc.), in order to identify a significant change which is indicative of a developing fault.

Condition-based maintenance is a kind of proactive maintenance. Compared with traditional reactive maintenance, it can not only improve operational availability, but also reduce the unnecessary scheduled maintenance cost, reduce the spare parts inventory cost, and minimize the life-cycle cost. However it can not be applied to every system. CBM can be applied in systems that (1) can be regarded as being deterministic to some extent. (2) is stationary or static, and (3) for which signal variables that can be good health indicators can be extracted.

With the development and advancement in censoring technology, data collection storage and processing capabilities, and continuous improvements in algorithms and data analysis techniques, CBM approaches is developing and improving. Currently, more and more focus has shifted to prognostics and health management which focus more on incipient failure detection, current health assessment and remaining useful life prediction. Figure 2.1 illustrates the relationship between CBM and PHM. According to Kalgren et al. (2006), PHM is a health management approach utilizing measurements, models, and software to perform incipient fault detection, condition assessment, and failure progression prediction. Lee et al. (2014) considers PHM as an evolved form of CBM, and CBM techniques can be used as input for the prognostics models in PHM and support the timely, accurate decision making.

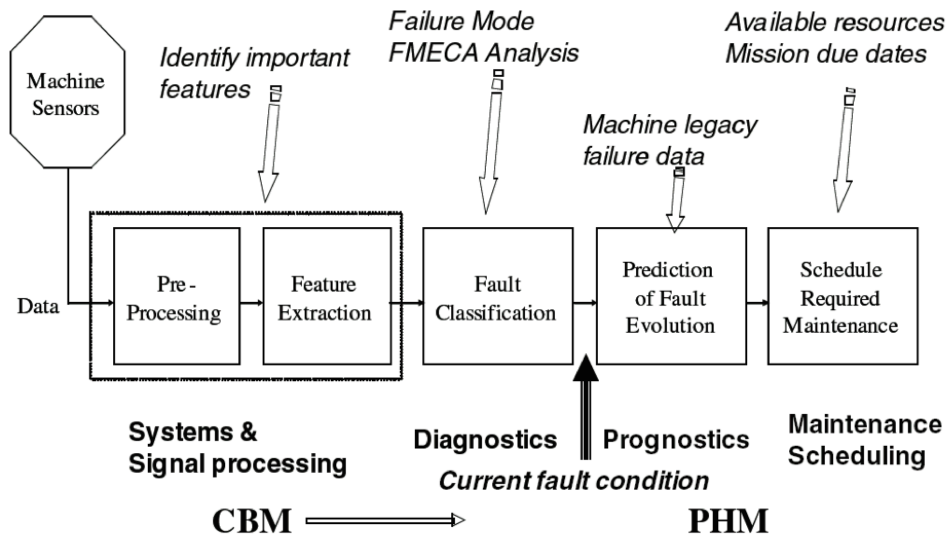

Figure 2.1: Stages within Prognostics and Health Management systems , adapted from Hess et al. (2006)

2.2 Content of Prognostics and Health Management

According to E. Lunde and Spjøtvold (2010), PHM primarily consists of two main technologies: health assessment and health management. Figure 2.2 illustrates the contents within each suite and their interaction. As shown in the figure 2.2, the typical capabilities in health management include diagnostics, prognostics, and anomaly detection, while the capacities in health management include decision-making, optimization and scheduling. Health assessment is a bottom-up analysis of a device and the analysis is at components or subsystems level, and it assumes that the state of the device can be explained by the state of its components. In contrast, health management is a top-down method, which utilizes the information obtained from health assessment to explore, evaluate and propose appropriate decisions along with operational, maintenance, supply chain and other logistics related aspects, in order to maintain the desired system performance and meet requirements and constrains. Logistics issues like repair scheduling, operational reconfiguration, spare allocation, customer notification are also included inside the health management.

Prognostics and Health Management has been applied to Aerospace and Military systems for more than 20 years. Early on, the concept was simply to detect and report failures – basic Built-

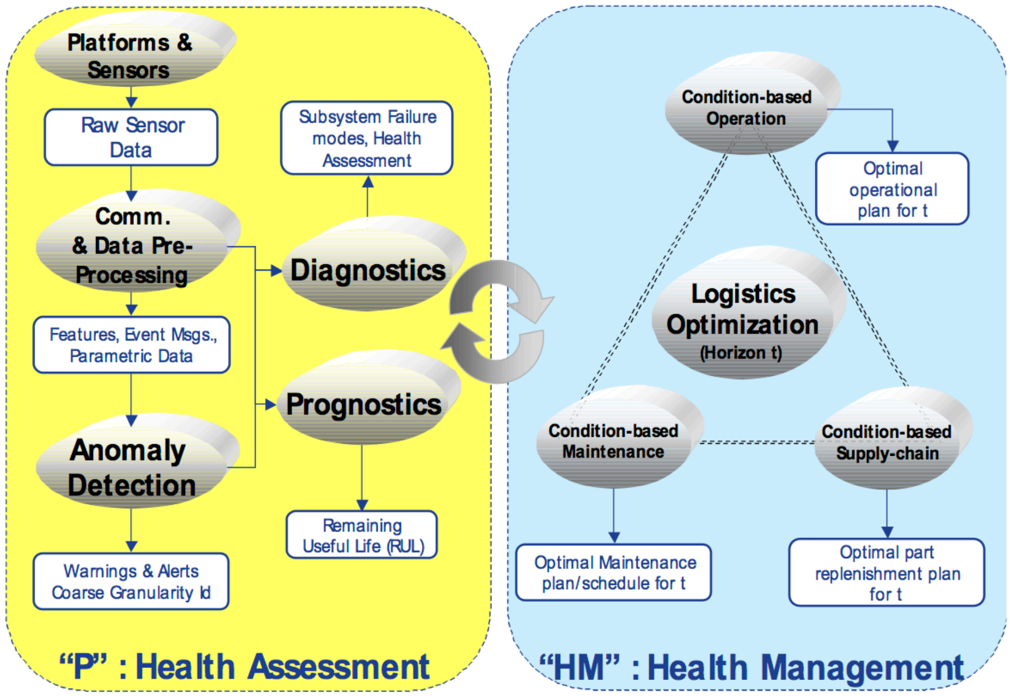

Figure 2.2: Two main issues of Prognostics and Health Management
, adapted from E. Lunde and Spjøtvold (2010)

In-Test. And it gradually grows into more sophisticated technologies and methods for evaluating the health of equipment and for using the results to direct and support maintenance. Hess et al. (2006) describes that PHM is developed for the new F-35 Joint-Strike Fighter(JSF), enabling the vision of autonomic logistics and helping to meet the overall affordability and supportability goals of the latest military fighter aircraft. So far, a lot of prognostics methods and systems have been developed for machinery maintenance. The academic research focus mostly on remaining residual life estimation, but it is only one part of the prognostics. Hess et al. (2006) lists some functionalities and capabilities that might be contained within a modern PHM system, as shown below:

- Fault detection / isolation
- Advanced diagnostics

- Predictive prognostics
- RUL and time-to-failure predictions
- Component life usage tracking
- Warranty guarantee tracking
- Health reporting and information management
- Utilization tracking
- Decision support systems
- Fault accommodation
- Information fusion and reasoners

2.3 Procedure of PHM

2.3.1 FMECA analysis

The fist step of PHM system development is to implement a comprehensive FMECA study. The objective is to relate failures to the root causes. Through FMECA studies, all potential failure modes, the severity of them and the probabilities of occurrence, the fault symptoms and the monitoring methods and sensors required will be covered in the analysis at component level or subsystem level.

Butler (2012) claims that FMECA are often used as the starting point of development of fault diagnostics capabilities, and it typically requires input from variety of sources including domain experts, maintenance personnel, equipment specialists and designers.

2.3.2 Data Acquisition

According to Jardine et al. (2006) data acquisition is a process of collecting and storing useful data(information) and it is an essential step for fault diagnostics and prognostics. And Data could be categorized into two types, namely event data and condition monitoring data. Event data includes the information on what happened and what was done to the systems or equipments. while condition monitoring data can be the measurements related to the condition of the equipment. In practice, event data always need manual data entry to the information systems and sometimes may be neglected by personnel, but event data and condition monitoring data are equally important.

With the rapid development of the computer and sensor technologies, more and more powerful data acquisition techniques is becoming affordable. The most common monitoring data can be vibration data, acoustic data, oil analysis data, temperature, pressure, humidity, moisture, weather or environment data, etc. Various sensors have been designed for data collection, such as micro-sensors, ultrasonic sensors, acoustic emission sensors. This thesis will not cover the detail about data acquisition techniques, but books like Nikolay V. Kirianaki (2002) and Austerlitz (2002) will provide more details.

2.3.3 Data processing

Data cleaning

The first step of data processing is data cleaning. This is an important step since data, especially event data, which is usually entered manually, always contains errors. Data cleaning ensures, or at least increases the chance, that clean (error-free) data are used for further analysis and modeling. Data errors are caused by many factors including the human factor and sensor faults. In general, however, there is no simple way to clean data. Sometimes it requires manual examination of data. Graphical tools would be very helpful to finding and removing data errors. Data cleaning is, indeed, a big area. It is not in the scope and will not be discussed in detail here.

Data analysis

The next step of data processing is data analysis. Jardine et al. (2006) categorizes condition monitoring data into three categories: value type, waveform type, and multi dimension type. Value type data is single value, like temperature, pressure, etc. Waveform data is like vibration signals and acoustic emissions, motor current, partial discharge, etc. An example for multidimensional type data is the image data. A variety of models, algorithms and tools are available in the literature to analyze data for better understanding and interpretation of data. The models, algorithms and tools used for data analysis depend mainly on the types of data collected. For example, for waveform data analysis, frequency-domain analysis obtained by transformation from time domain, can easily identify and isolate certain frequency components of interest. For detail introduction about time-domain, frequency domain and time frequency analysis methods, check the article Jardine et al. (2006).

2.3.4 Diagnostics

Fault diagnostic, according to George Vachtsevanos (2006), is the foundation of the condition-based maintenance, and it is designed to detect system performance, monitor degradation levels, and identify faults based on physical property changes, through detectable phenomena.

Early diagnostic was developed in the form of built-in-test(BIT) equipment in the aircraft. Built-in test is defined as an on-board hardware-software diagnostic means to identify and locate faults, and includes error detection and correction circuits. Later on fault diagnostic capability has bee improved due to the continuous improvement in computer power and data storage capabilities.

The term fault diagnostics is used to describe a range of tasks and capabilities and it has not yet been well defined. The following definition is given by George Vachtsevanos (2006):

☞ **Fault diagnosis**: Detecting, isolating, and identifying an impending or incipient failure condition-the affected component (subsystem, or system) is still operational even though at a degraded mode.

Failure diagnosis: Detecting, isolating, and identifying a component (subsystem, or system) that has ceased to operate.

Fault (failure) detection involves identifying the occurrence of a fault, or failure, in a monitored system, or the identification of abnormal behavior which may be indicative of a fault condition.

Fault (failure) isolation involves identifying which component/subsystem/system has a fault condition, or has failed.

Fault (failure) identification involves determining the nature and extent of a system fault condition or failure.

2.3.5 Prognostics

Diagnostics is conducted to investigate or analyze the cause or nature of a condition situation or problem, whereas prognostics is concerned with calculating or predicting the future as a result of rational study and analysis of available data. Prognostics has the ability to identify the presence of incipient fault conditions and incipient faults identification enables maintenance personnel to potentially avoid the catastrophic failures. Butler (2012) considers prognostics as a more difficult task than diagnostics since evolution of equipment fault conditions is subject to stochastic processes and in addtion prognostics involves a large degree of uncertainty. The figure 2.3 describes a clear relationship between diagnostics and prognostics according to the propagation of the fault.

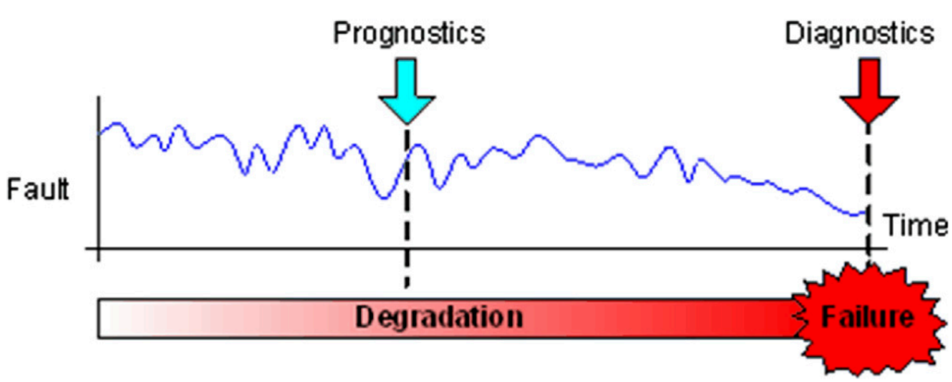

Figure 2.3: Diagnostics and Prognostics, adapted from Lee et al. (2014)

The standard ISO 13381-1 introduces a definition of prognostics, which is an estimation of time to failure and risk for one or more existing and future failure modes. The most common prognostics is to predict how much time left before a failure (or a fault) occurs given the current machine condition and past operation profile. The time left before failure is called remaining useful life(RUL). Except for RUL prediction, the probability that the machine can survive until next inspection given the current condition and history operation profiles is also a good reference for maintenance personnel to make decisions.

2.3.6 Decision making

the results from prognostics such as residual useful life with its confidence level and the probability of failure before next inspection is the vital information for supporting the maitnenacen decision making. Except for that, there are also other issue should be taken into consideration, such as the availability of spare parts and specific tools, human resources, economic costs, maintenance strategy, regulations and laws, etc. Hence, a robust maintenance decision making system is needed to balance the different profits and boundaries. Jardine et al. (2001) introduces the EXAKT software for optimizing maintenance decisions for the mine haul truck wheel motors. EXAKT not only considers the results from prognostics but also considers the cost function, replacement policy, hazard sensitivity and cost sensitivity for making decision.

2.4 Diagnostics methods review

As discussed in last section diagnostics is the basis of prognostics and has been deeply researched. In this section common diagnostics methods that has used are briefly reviewed, and more focus is given to prognostics. According to George Vachtsevanos (2006) fault diagnosis methods can be classified into two types, model-based and data-based approaches. In the following both two types will be introduced.

2.4.1 Model-based approaches

Model-based fault diagnostic approaches utilize a mathematical model of the system under observation. The estimated results generated by the model are then compared with the actual process outputs, and the potential fault conditions are identified based on the residual value. The model being utilized is derived from fist principles, and embodied by series of dynamic equations that define relationships, at a given time or load cycle, between damage (or degradation) of a system or component and environmental and operational conditions under which the system or component are operated. Figure 2.4 illustrates the basic concepts of a typical model-based approach to fault diagnostics.

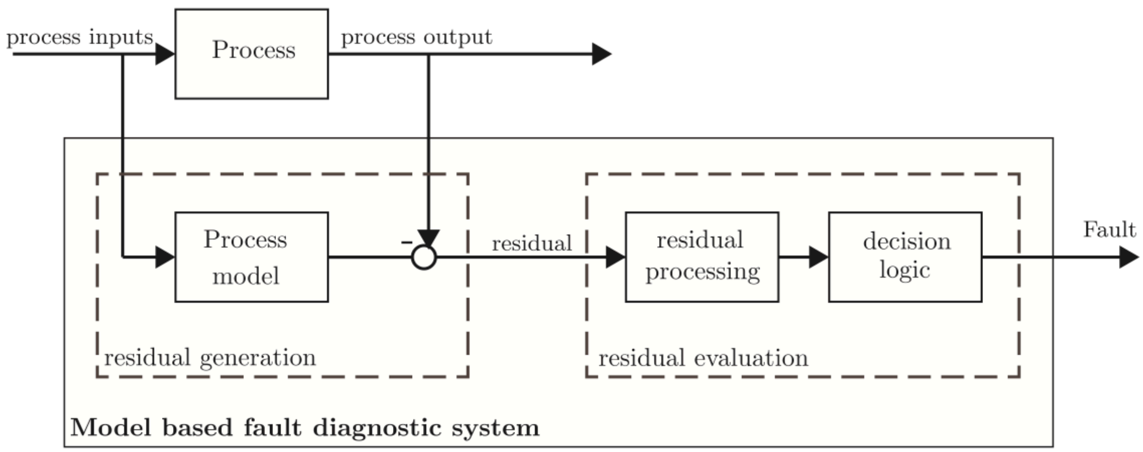

Figure 2.4: Model-based Diagnostic Approach

As illustrated in figure 2.4, a residual is generated after the comparison of actual system output and the model estimate. For normal operation, the value of residual signal should be approximately zero, while when the value of the residual signal is deviated from zero, the residual signal will be forwarded to a decision logic routine which is used to map the behavior of the residual signal onto a specific fault condition.

2.4.2 Data-driven approaches

The general principle of data-driven approaches to fault diagnostics is to utilize pattern recognition techniques to map data in the measurement, or feature, space, to equipment faults within the fault space. And data-driven approaches is categorized into two types, namely statistical approaches and artificial intelligence based approaches by Jardine et al. (2006).

Statistical approaches has some common methods, such as statistical process control(SPC), principal component analysis(PCA), and partial least squares(PLS).

Statistical process control, SPC, which was originally developed in quality control theory, has been well developed and widely used in fault detection and diagnostics. The principle of SPC is to measure the deviation of the current signal from a reference signal representing the normal condition to see whether the current signal is within the control limits or not. Gallagher et al. (1997) uses SPC for semiconductor chamber damage detection

Principal component analysis, PCA, is often applied to high-dimensional datasets to transform a number of related variables to a smaller set of uncorrelated variables. According to Venkatasubramanian et al. (2003), the basic principle of PCA for fault diagnostics is to derive a PCA model using a dataset of normal fault-free behavior. Future observations are then compared with this model using statistical measures such as the T^2 and Q statistics. If the measured statistics exceed a defined limit, a potential fault condition is flagged.

Partial least squares, PLS, is a multivariate regression algorithm based upon PCA. Whilst PCA is concerned with decomposing an input matrix X into its principal components, PLS is concerned with developing a linear regression model by first projecting the input matrix X and output matrix Y onto a lower dimensional space. Qin (2009) gives a contemporary review of applications of PCA and PLS to fault diagnostics.

Cluster analysis, as a multivariate statistical analysis method, is a statistical classification approach that groups signals into different fault categories on the basis of the similarity of the characteristics or features they possess. It seeks to minimize within-group variance and maximize between-group variance. The result of cluster analysis is a number of heterogeneous groups with homogeneous contents: There are substantial differences between the groups, but the signals within a single group are similar.

AI approaches for diagnostics includes artificial neural networks(ANNs), support vector classification, and fuzzy logic. And the detail of ANNs will be discussed in next section.

2.5 Prognostics methods review

Due to the variety of techniques that are applied into prognostics problems, it is not easy to categorize different approaches into different classes. George Vachtsevanos (2006) categorizes prognostics approaches into three classes, experience-based, data-driven and model-based approaches. Figure 2.5 illustrates how we move from experience-based to model-based approaches, with increasing capability and performance. However, George Vachtsevanos (2006) points out that the applicability seems to be decreasing.

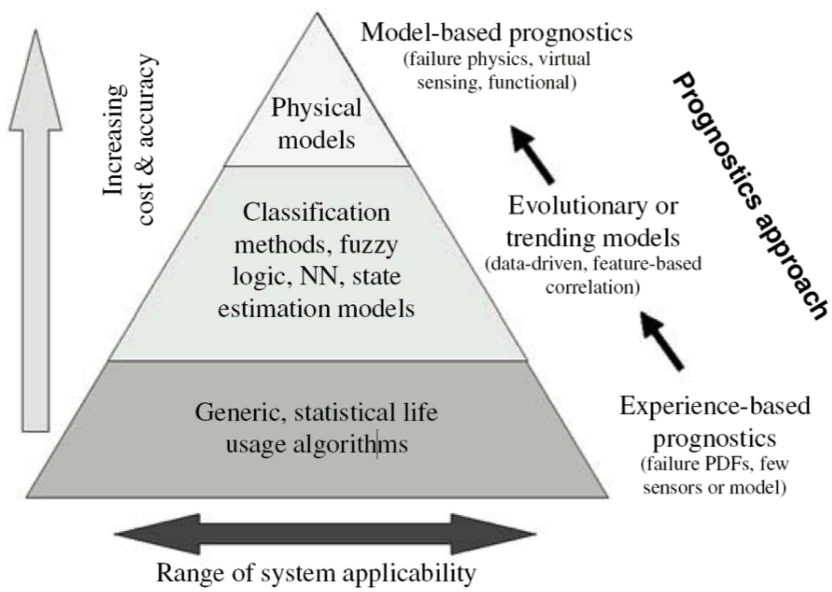

Figure 2.5: Technical approaches to prognostics, adapted from George Vachtsevanos (2006)

In the following sections, a brief review of these three classes of approaches is presented, and relevant applications of different approaches will also be discussed.

2.5.1 Experience-based prognostics approaches

The simplest prognostics approaches reply on statistical information that are collected from event records of a big population of identical items and used to examine historical failure rate of systems or components. And these data can be used for developing life-usage models in terms of distribution of failure rates over time. Rausand and Høyland (2004) has introduced many parametric statistical models, such as Exponential, Weibull, Normal, Log-normal, Logistic, Log-logistic and Gamma distributions. And the Exponential and Weibull distribution are the most common used distributions among them. The former is very simple and easy to apply and the later has the ability to adjust to varies types of failure rate in different phases, like infant, mature, wear out phases.

The conventional experience-based approach is used for preventive maintenance scheduling based on the mean time between failure(MTBF). However, these approaches do not have predictive capability and are not the real prognostics techniques. In general, these approaches can be applied widely in systems or components with low criticality and cost, or in the situation where the sensor data is not available. The following data-driven and model-based methods are developed for individual component or system prognostics.

2.5.2 Data-driven method

Data-driven approaches attempt to derive models directly from routinely collected condition monitoring data instead of building models based on comprehensive system physics and human expertise. They are built based on historical records and produce prediction outputs directly in terms of CM data, so that it only needs the certain amount of data, and it does not require comprehensive understanding of the system . However, the main drawback of this approach is that its effectiveness and accuracy is highly dependent on the quantity and quality of operational data used to build the model. While, data driven models are considered to be the most popular method for prognostics.

Data driven approach can be divided into three major categories: Artificial Intelligent (AI) methods; stochastic process based models; and covariate based hazard models. Figure 2.6 lists most of the date-driven method for prognostics.

Time series approaches

The conventional data-driven methods rely on simple projection models, which project the current level of degradation into the future. Such common used approaches can be exponential smoothing techniques (Byington and Roemer (2002)) and autoregressive model (Wu et al. (2007b)). One major advantage of these techniques is the simplicity of their calculations, which can be carried out on a programmable calculator. However, the limitation of these trend forecasting techniques is the assumption of some underlying stability in the monitored system and relying on past patterns of degradation to project future degradation.

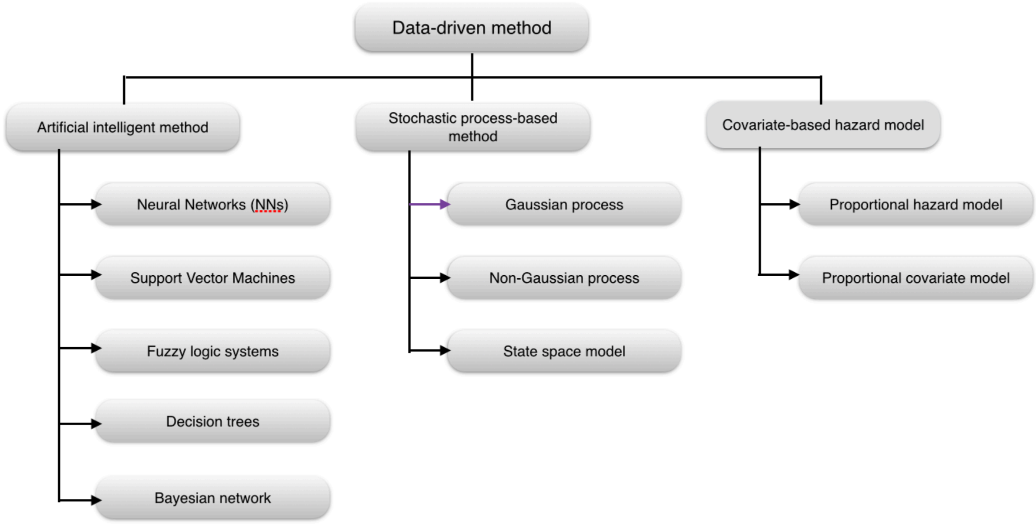

Figure 2.6: Data-driven methods for Prognostics,

Artificial intelligent methods

Artificial intelligence has been increasingly applied to machine diagnostics and prognostics. In literature A.Poongodai and S.Bhuvaneswari (2013) and Schwabacher and Goebel (2007) there has listed many AI methods, such as machine learning techniques(e.g. Neural Networks(NNs) and Support Vector Machines(SVM)), knowledge based techniques(Expert Systems(ESs) and fuzzy logic systems), and graphical techniques (decision trees, Petri Net, and Bayesian Networks). In the following content a brief introduction of some artificial intelligent methods will be given, while Neural Networks will be discussed in detail in chapter 3 since its simplicity and popularity.

Artificial neural network(ANN) is the most common and traditional machine learning techniques. It can be used for classification(e.g. failure diagnostics) and prediction (e.g. failure prognostics) problems. Feedforward NNs and recurrent NNs are two typical structures of Neural Networks. The common used activation functions of the neurons for forecasting are radial-basis function networks polynomial and wavelet. Gebraeel et al. (2004) estimated the bearing failure time using a feedforward NN model. Wu et al. (2007a) developed an integrated feedforward NN model that uses sensory information to predict the life percentage of a rotating machine. Vachtsevanos and Wang (2001) develop a recurrent wavelet neural network to predict rolling element bearing crack propagation.

Support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. It is relatively new and complex machine learning techniques that overcomes the overfitting problem of NNs. Widodo and Yang (2007) has reviewed and summarized the recent research and developments of SVMs in machine condition monitoring. Li et al. (2007) has used a SVM approach to predict the condition residual life.

Stochastic process based models

Stochastic process based models are developed to describe degradation of an asset using suitable stochastic process. Gaussian and non-Gaussian process are common underlying degradation process that were applied in prognostics issue.

The Wiener process (Brownian motion with drift) is a well-known Gaussian process. It is a continuous-time Markov process with independent increments. Wiener process originally was developed to model the movement of small particles in fluids and air, so the increments can be either positive or negative, while in reliability issue, some pattens are only monotone, such as fatigue crack propagation, creep, and the amount of erosion. Also, Wiener process is a time homogeneous process, but the degradation process may not have this nature.

One common non-Gaussian process is Gamma process. Gamma process is a natural model for degradation processes where deterioration is supposed to take place gradually over time in a sequence of tiny positive increments. In theory, Gamma process has 3 properties: (1) the increments $Y(t_i) - Y(t_{i-1})$ for a given time interval Δt has a gamma distribution; (2) The increments in any disjoint time intervals are independent random variables; (3) $Y(0) = 0$. Lawless and Crowder (2004) applies a Gamma process model to fatigue growth problem, Pandey et al. (2005) has compared the random variable deteriorate model with Gamma process model for aging structural components.

Compound Poisson process is a continuous-time Markov process with non-negative, stationary, and independent increments. The main difference from Gamma process is Compound Poisson process has a finite number of jumps in finite time intervals. And Compound Poisson process is suitable for modeling usage such as damage due to shocks.

State-space models are models that use state variables to describe a system by a set of first-order differential or difference equations. State variables x(t) can be reconstructed from the measured input-output data, but are not themselves measured during an experiment. General state models are represented by the following equations:

$$x_t = F_t(x_{t-1}, w_t) \tag{2.1}$$

$$y_t = H_t(x_{t-1}, v_t) \tag{2.2}$$

Where the y_t is observed state value, x_t is the unobserved state process, F_t and H_t are arbitrary functions.

State space models are appropriate for handling multivariate data, linear Gaussian process and nonlinear-Gaussian process. According to J. Durbin. (2012) the advantage of state space models is the ability to model the behavior of different components of the series separately and then put the sub-models together to form an overall model for the series. When the state variables are discrete, it is often called Hidden Markov Model (HMM).

Covariate-based hazard models

In practice, wear out of mechanical components or deterioration of electrical devices is caused by one or more factors, and these factors are called covariates, for example, temperature, humidity, pressure, etc. These covariates change stochastically and may influence and or indicate the lifetime. Therefore, it is important to incorporate these covariates into lifetime modeling. condition monitoring can record the change of these covariates. Considering the condition monitoring data together with the historical failure data,is the advantage of covariate-based hazard models. Proportional hazard model is one common used model and it has been used in various applications (e.x. Jardine et al. (2001), Kumar and Westberg (1996)).

2.5.3 Model based method

Model-based approaches is also called physics-based model. Prognosis of remaining useful life (RUL) is carried out based on knowledge of the processes causing degradation and leading to failure of the system. It combines a physical damage model with measure data to predict future behavior of degradation or damage as illustrated in figure 2.7. The RUL is estimated by progressing the damage state reaches the threshold.

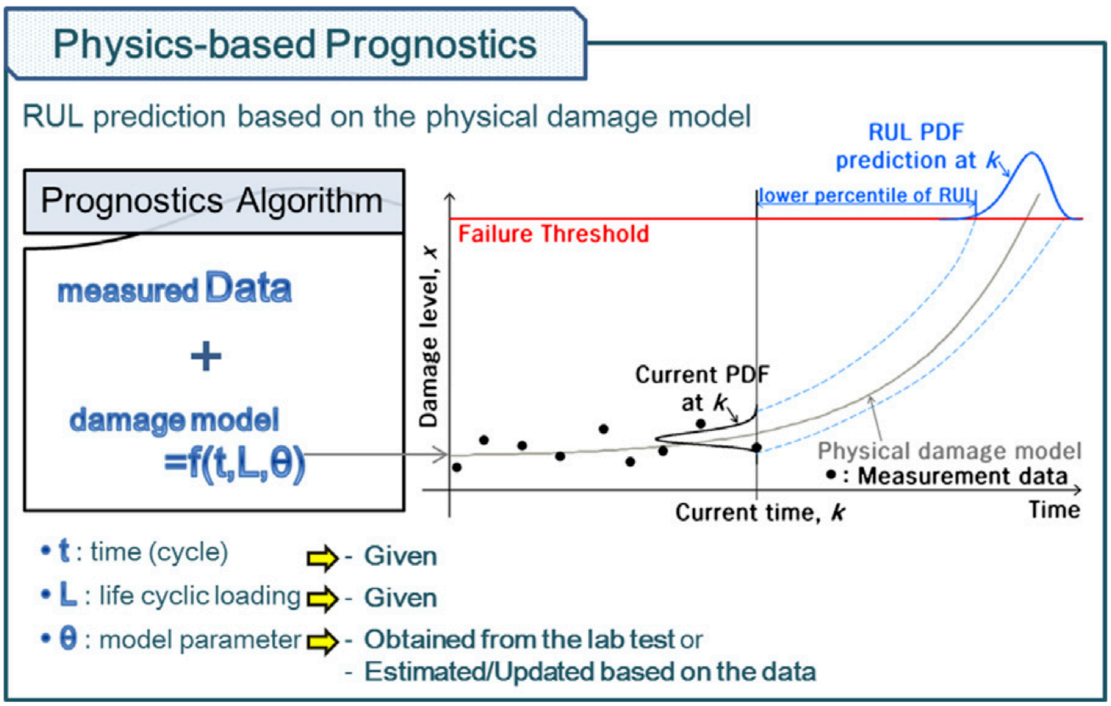

Figure 2.7: Illustration of Physics-based prognostics

The main advantage of physics-based approach is that the model represents the physical features of the machine that are more visualized and understandable for the maintenance personnel. In addition, the physics-based model can produce more accurate results than data-driven models, especially for long-term prediction.

On the other hand, since the models contains some assumptions and approximations, it required to be validated before applying. And secondly, as the model increases, the number of parameter also increases, which will lead estimation of parameter very difficult. However, parameter identification and estimation is the most important issue because the behavior of a physical model depends on the model parameter estimation. Thirdly, sometimes the system is so complex that a mathematical model can not be developed from the first principles. Finally, due to the variate principles, different components should use different models. The process of building models requires the personnel to have a very deep understanding of the system and it is also very time consuming and costly.

Chapter 3

Proposed hybrid model for degradation prognostics

In last chapter both of model-based and data-driven prognostics methods has been discussed and compared. Unlike model-based prognostic method, data-driven prognostic approaches are much more practicable to implement for industries because data-driven methods are easy to understand and mostly there are a big amount of monitoring data existing. Within data-driven methods, artificial neural networks (ANNs) and Stochastic process based models are relatively new in applications in the reliability field and have not yet been effectively applied in remaining asset lifetime prediction problems. These models are promising to demonstrate both linear and nonlinear relationships between covariate data and actual asset health. In this chapter these two methods will be used to deal with the degradation prognostics.

Degradation or deterioration problem is a common issue either for machinery or electronics. Currently, the industry common strategy for degradation is using model-based diagnostic method to send alarm if something goes wrong, however, the need to maintain high availability of the system is necessary, which means maintenance planning in advance is prerequisite. Therefore the prognostic ability becomes more important and imperative.

3.1 Propose a hybrid model

For machinery, many researches has been done on degradation relevant issues. The conclusion is the Gamma process is the most suitable model for monotonic degradation issues, such as corrosion, erosion, crack propagation, etc. Gamma process is a suitable method for predicting the trend of degradation with stochastic property. Nevertheless, the assumption always made for gamma process is that the degradation status is directly observed. In fact the indicator sometimes is not observable. For example subsea equipments are located on the seabed and difficult for retrieval and inspection. It is difficult and time-consuming and also very costly. The problem of degradation indicator selection and extraction has not yet been studied much so far. This paper is going to discover the method for solving the gamma process application limitation.

As the condition monitoring technology is developing fast and being applied in various industries, it becomes easier for the degradation visualization. The degradation level is not directly detected, but it is possible to monitor the relevant covariates that can be fused into a parameter that indicates current status of the monitored system or component. For example DWS team introduces that the tire deflation is detected not directly by the air pressure, instead, Dunlop Tech monitors the wheel speed to indicate the deflation.

The relationship between the degradation indicator and its relevant covariates can be either linear or non-linear, and it is normally derived from the first principles. Ideally the trend of degradation indicator should be monotonic due to the property of the degradation, but in reality, the results of the degradation parameter will always varies, with a lot of noise.

The non-monotone degradation parameter calculated from the monitoring data, needs to be processed by techniques such as filtering and smoothing. When data processing is done, the relationship between the history monitoring data set (measurable covariates) with these post-processed values of degradation parameter could be built by ANNs model to replace the original physics-orientated relation. The post-processed degradation parameter values are used as the output of the ANNs, and the values of the measurable variables are fitted in ANNs as inputs. The ANNs is trained with a certain amount of the history data sets. After training, if the future measurable variables are collected and putted into the ANNs model, the degradation parameter value can be obtained from the new output of ANNs, which infers the health condition of components or subsystems. The new output sets are the target values that is assumed as a gamma process and used for prognostics. The technical road map of this method is shown in the figure 3.1:

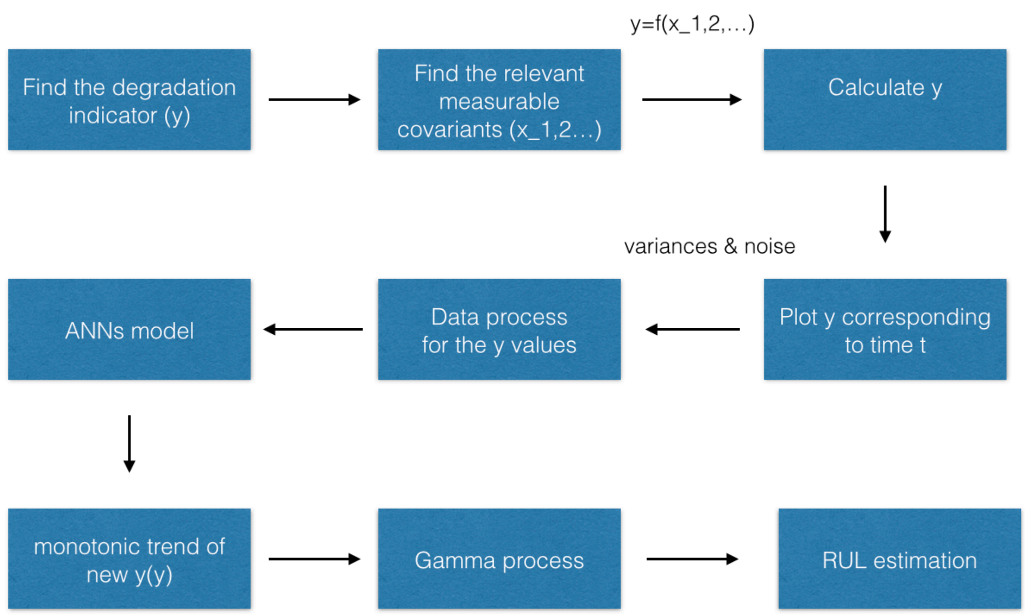

Figure 3.1: The procedure of proposed method for degradation problem

In a word, a hybrid model is proposed with Artificial Neural Network for degradation state visualization and Gamma process for degradation prognostics. And in the following content, the theory of Artificial Neural Networks and Gamma process will be discussed in detail.

3.2 Artificial Neural Network

As described in previous chapter, artificial neural network is a flexible model that can be used for nonlinear modeling. ANNs model relationships between input and output variables with a model structure inspired by the neural structure of the human brain.

According to Heng et al. (2009), an ANN consists of a layer of input nodes, one or more layers of hidden nodes, one layer of output nodes and connecting weights. The network learns the unknown function by adjusting its weights with repetitive observations of inputs and outputs. After the training process, the validation should be done using another sets of history data before ANN is used for prediction.

Neural network can be classified into two major types: the static neural network and the dynamic neural network. Static neural networks have no feedback elements and contain no time delays. Contrary to the static neural network, the dynamic neural network, the output depends on the current or previous inputs, outputs or states of the networks. Moreover, dynamic network can be divided into two subgroups: Dynamic networks with feed-forward connections, where the output response depends both on inputs and time; dynamic networks with feedback or recurrent connections, where the output depends on the previous states and time. For example, recurrent neural networks (RNNs), according to Boden (2001), have one or more feedback loops and it has the ability to store the preceding states and record the characteristics of a system it represents over time. The figure 3.2 shows an illustrative example of the general structure of a recurrent network.

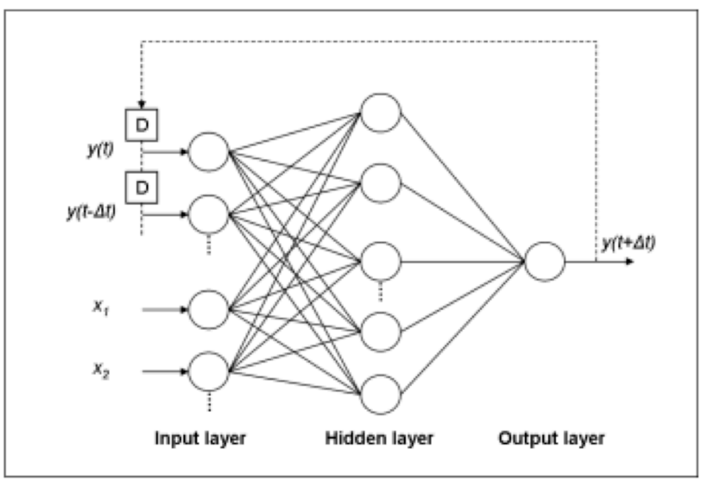

Figure 3.2: Recurrent Neural Network

Since the ANNs is not going to applied for prediction in this paper, the recurrent neural networks will be not discussed here. In the following the feed-forward neural network (FFNN) is introduced.

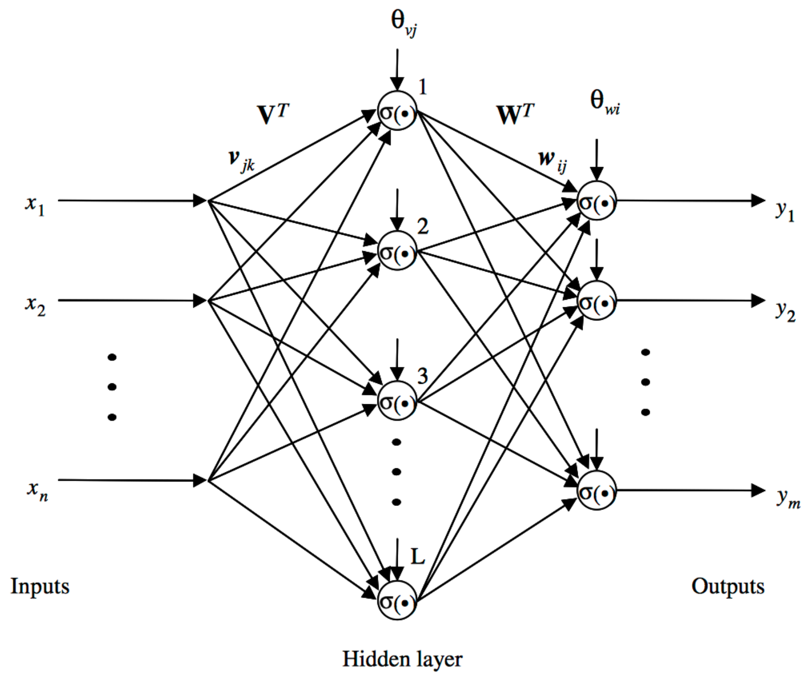

Figure 3.3: Two-layer neural network

3.2.1 Feedforward neural network

Figure 3.3 shows the typical structure of two layer feed-forward neural network. The value x_k are the inputs, and y_i are its output. Function σ(ů) is a nonlinear activation function contained in the hidden-layer. The hidden layer weights are v_{jk}, and its bias values are θ_{vj}. The output layer weights are w_{ij} and bias values are θ_{wi}. The number of hidden layer neurons is L.

The neuron computes the weighted sum of the inputs and adds a bias value θ. The results are then delivered to the activation function in the neuron σ(ů), to yield the neurons outputs. After that, the neuron outputs are then passed as an input to the next layer, here namely the output layer, the outputs of the hidden layer will be transfered again by the activation function in the output layer. A mathematical formula descrying the NN is given by

$$y_i = \sigma(\sum_{j=1}^{L} w_{ij}\sigma(\sum_{k=1}^{n} v_{jk}x_k + \theta_{vj}) + \theta_{wi}) \tag{3.1}$$

Activation functions

There is a variety of linear or non-linear activation functions in the neurons and some common ones are step function, log-sigmoid, and tan-sigmoid functions, radial-basis, ridge polynomial, wavelet functions. A.Poongodai and S.Bhuvaneswari (2013) claims that log-sigmoid activation function is often used in output layer for classification problems, to limit the output to a small range, whilst linear activation function is often used in output layer for regression problems, to avoid limiting the output range.

Network Training

A network training procedure is to identify the optimal set of weights and bias values for each neuron, given a set of input and output training data. The most common training approach is the back propagation algorithm, and the procedure of network training is described here:

(1) The first step is put the training data into the network, and networks weights and bias are randomly generated, and output can be calculated;

(2) The second step is to compare the model output y_i with the target value $\hat{y}_i$ from the data set, and the sum of squared error(SSE) is computed as below:

$$SSE = \sum_{i=1}^{n} \sum_{j=1}^{m} (y_i - \hat{y}_i) \tag{3.2}$$

where n is the number of input-output samples in the training data set, m is the number of outputs.

(3) The next step is to evaluate the error and minimize the SSE by modifying the weights between each neuron. A common weight-tuning algorithm is the gradient algorithm based on back-propagated error. This algorithm is given by:

$$\mathbf{W_{t+1}} = \mathbf{W_t} + \mathbf{F}\sigma(\mathbf{V_t^T X_d})\mathbf{E_t^T} \tag{3.3}$$

$$\mathbf{V_{t+1}} = \mathbf{V_t} + \mathbf{G X_d}(\sigma_{\mathbf{t}}^{'\mathbf{T}} \mathbf{W_t E_t})^{\mathbf{T}} \tag{3.4}$$

Where **t** is the time index, and $\mathbf{E_t} = \mathbf{y_d} - \mathbf{y_t}$ is the output error at time t, $\mathbf{y_d}$ is the output value from the training data set, $\mathbf{y_t}$ is the model output at time t. **F** and **G** are weighting matrices selected by the designer that determine the speed of convergence of the algorithm.

(4) The training process is then repeated until the error reaches a desired threshold value, or until the required number of training iteration has been done. At that time, the network is deemed to have done with training, and can be used for prediction.

3.2.2 NNs merits and limitations

Merits

According to Heng et al. (2009), numerous studies from various disciplines have demonstrated the merits of ANNs:

a) It performs faster than system identification techniques in multivariate prognosis;

b) Its performance is at least as good as the best traditional statistical methods, without requiring untenable distributional assumptions [33,34];

c) It is able to capture complex phenomenon without a priori knowledge.

Limitations

a) The first issue is the selection of the network architecture. There is always problems to determine the number of neurons should be contained in the network, as well as the number of layers. Lawrence has utilized the mean square errors in order to find the optimal number of neurons. Ostafe introduces a method to determine the number of hidden layers by using pattern recognition. However, there is still no standard method. It is often a trial and error exercise. More neurons within the network, more powerful the ability of network to model more complex relationship. However, more neurons maybe lead to over fit the data, and the generalization capability will reduce. Many issues should be considered during network size selection.

b) Finding the optimal parameters is another problem for neural networks. As known for more complex system the network will contain more neurons. It is extremely difficult to find global optimum if there are many parameters, especially for back propagation.

c) The uncertainty caused by the noise in the data is not considered in neural network. And there is no parameters related to the noise of data. For the noise in the data, it is common to provide the confidence bounds. Few works has been done on probabilistic neural network in order to handle the uncertainty. Khawaja introduces a way to obtain confidence bounds and also confidence distributions. The ability of handling noise of data is still need to be improved to build confidence.

d) Lacking of transparency is also an issue that is argued by many authors. However, Bostwick and Burke (2001) argues that the transparency will reduce when model complexity increase for both of traditional statistical models and ANN models. It is just that ANNs are more capable in modeling complex phenomenon and consequently need a more complex structure to represent the phenomenon.

e) There is no clear documentation shows how the decisions are reached in a trained neural network, since NNs are the black box . While, Thong (2000) argues that rules can actually be extracted from trained ANNs to explain how decisions are reached.

3.3 Stochastic Process

As discussed in chapter 2.6, the stochastic process is a very powerful method to model the temporal uncertainty associated with the evolution of deterioration. And the common used stochastic process are Gamma process, Wiener process and Levy process. Since most of the degradation is monotone and random, which makes Gamma process most suitable model for analyzing the wear and fatigue propagation, corrosion, erosion, etc. And it overcomes the problem of random coefficient regression based model. The regression based model is simple to implement but they are lacking of temporal randomness even if they use nonlinear regression, and also the regression based model may not be able to derive a closed-form expressions for time to failure(TTF) distribution or residual useful life (RUL) distribution.

In the Gamma process model, the cumulative deterioration $X(t)$ at time t follows a gamma distribution, with a shape function $\lambda(t) > 0$ and a scale parameter $u > 0$, which is a constant value. Since gamma process has the monotonic property, the shape function $\lambda(t)$ is required to be increasing function of time t, and also $\lambda(0) = 0$. The probability density function of the cumulative deterioration is given as

$$f_{X(t)}(x) = \frac{u^{\lambda(t)}}{\Gamma(\lambda(t))} x^{\lambda(t)-1} e^{-ux} = Ga(x|\lambda(t), u) \tag{3.5}$$

The mean value $E(X(t))$, the variance $Var(X(t))$, and the coefficient of variance (COV) $COV(X(t))$ of the cumulative deterioration at time t are given as

$$E(X(t)) = \frac{\lambda(t)}{u}, Var(X(t)) = \frac{\lambda(t)}{u^2}, COV(X(t)) = \frac{1}{\sqrt{\lambda(t)}} \tag{3.6}$$

For the deterioration process, normally the item is assumed to be failed if the deterioration level reached a specific value, and this level is called critical deterioration level, which can be denoted as L. So the probability of failure can be derived as

$$Pr(T \leqslant t) = Pr(X(t) \geqslant L) = \int_L^{\infty} f_{X(t)}(x)dx = \frac{\Gamma[\lambda(t), uL]}{\Gamma[\lambda(t)]} \tag{3.7}$$

The damage increment from time τ to t, represented by $X(\tau) - X(t)$, is a non-negative quantity that is independent of the cumulative deterioration at time t, $X(t)$. The increment is also a gamma distribution with shape function $\lambda(\tau) - \lambda(t)$, and the scale parameter u as a constant. That is because Gamma process has the properties that the increments are independent random variables also with gamma distribution. The probability density function of the increment $X(\tau) - X(t)$ is given as

$$f_{X(\tau)-X(t)}(x) = \frac{u^{\lambda(\tau)-\lambda(t)}}{\Gamma(\lambda(\tau) - \lambda(t))} x^{\lambda(\tau)-\lambda(t)-1} e^{-ux} = Ga(x|\lambda(\tau) - \lambda(t), u) \tag{3.8}$$

J.M. van Noortwijk (2004) claims that empirical studies show that shape function $\lambda(t)$ is proportional to a power law and it can be written as:

$$\lambda(t) = ct^b \tag{3.9}$$

where c and b are physical constants. For the parameter b, it can either be given by the experts or can be inferred numerically by maximum likelihood estimation. It is common to use expert judgment to get the value of b, for example, sometimes b equals to 1 for simplicity, which means $\lambda(t) = ct$. In this case, it is a stationary gamma process, where the average deterioration increases linearly with time. According to J.M. van Noortwijk (2004), the gamma process is not restricted to using a power law for modeling the expected deterioration over time. As a matter of fact, any shape function $\lambda(t)$ suffices, as long as it is a non-decreasing, right continuous, and real-valued function. So now the probability density function is

$$f_{X(t)}(x) = \frac{u^{ct^b}}{\Gamma(ct^b)} x^{ct^b-1} e^{-ux} = Ga\left(x|ct^b, u\right) \tag{3.10}$$

After substitute $\lambda(t)$ withct^b, the mean and variance is given as

$$E(X(t)) = \frac{ct^b}{u}, Var(X(t)) = \frac{ct^b}{u^2} \tag{3.11}$$

3.3.1 Parameter Estimation

The commonly used estimation methods are Probability Plotting, Least Squares, Maximum Likelihood Estimation and Bayesian Estimation Methods. A paper on Reliawiki said the method of maximum likelihood estimation method is, with some exceptions, considered to be the most robust of the parameter estimation techniques. In general, for a fixed set of data and underlying statistical model, the method of maximum likelihood selects values of the model parameters that produce a distribution that gives the observed data the greatest probability (i.e., parameters that maximize the likelihood function). Assuming we have n observations $x_1, x_2, .., x_n$. The principle of maximum likelihood assumes that the sample data set is representative of the population with a probability density function of $f(x_1, x_2, .., x_n; \theta)$ and chooses that value for θ (unknown parameter) that most likely caused the observed data to occur.

The maximum likelihood function can be setting up by using the independent increments $d_i = X(t_i) - X(t_{i-1})$ in interval (t_{i-1}, t_i), d_i is a product of independent gamma densities:

$$\begin{aligned} L(d_1, d_2, ..., d_n|c, u) &= \prod_{i=1}^{n} f_{X(t_i)-X(t_{i-1})}(d_i) \\ &= \prod_{i=1}^{n} \frac{u^{c(t_i^b - t_{i-1}^b)}}{\Gamma[c(t_i^b - t_{i-1}^b)]} d_i^{c(t_i^b - t_{i-1}^b)} e^{-ud_i} \end{aligned} \tag{3.12}$$

We know the cumulative amounts of deterioration at last inspection time t_n are measured as x_n, so the Expected value $E(X(t_n)) = x_n$. And since $E(x(t_n)) = \frac{ct_n^b}{u}$, the estimated value of scale parameter can be derived as

$$\hat{u} = \frac{\hat{c}t_n^b}{x_n} \tag{3.13}$$

3.3.2 Estimation of RUL

After estimating parameters of Gamma distribution function, the reliability function of time to failure could be deduced. For a single item, $R(t)$ is the probability of the deterioration level at time t smaller than the critical threshold L, and it can be derived as

$$\begin{aligned} &R(t) = Pr(T \geqslant t) \\ &= Pr(X \leqslant L) \\ &= Pr(X_t - X_0 \leqslant L) \\ &= \textstyle\int_0^L Ga(v|ct, u)\,dv \end{aligned} \tag{3.14}$$

Similarly, the conditional reliability function, given that at time the item is still functioning at time t_j can be given as

$$\begin{aligned} &R(t|T > t_j) = Pr(T \geqslant t|T > t_j) \\ &= Pr(X_t \leqslant L|T > t_j) \\ &= Pr(X_t - X_0 \leqslant L|X_{t_j} - X_0 < L) \\ &= \tfrac{\int_0^L Ga(v|ct,u)dv}{\int_0^L Ga(v|ct_j,u)du} \end{aligned} \tag{3.15}$$

Finally, the residual useful life distribution function $R_{RUL}(h)$ at time t_j can be derived as

$$\begin{aligned} &R_{RUL(t_j)}(h) = Pr(RUL(t_j) > h) \\ &= Pr(X_{t_{j+h}} < L|X_{t_j} < L, X_{t_j} = x_{t_j}) \\ &= Pr(X_{t_{j+h}} - X_{t_j} \leqslant L - x_{t_j}|X_{t_j} < L) \\ &= \tfrac{\int_0^{L-x_{t_j}} Ga(v|ch,u)dv}{\int_0^L Ga(v|\alpha t_j,\beta)dv} \end{aligned} \tag{3.16}$$

3.3.3 Merits and Limitations

Merits

a) Gamma process is a stochastic process and it can account for the population variability and temporal variability associated with a degradation process.

b) Gamma process has a straightforward mathematic calculations and it is easy to understand.

Limitations

a) Gamma process is only suitable for modeling the wear and fatigue issues, with a strictly monotonic process. Or this can also be the advantage of Gamma process in terms of monotonic process.

b) The degradation state should be observed directly. This can be solved by this hybrid model.

Chapter 4

Hybrid model application on subsea valves

Subsea industry is growing very fast in 21st century, since the easy fields in the world have already been explored, and the left oil and gas reservoir is far from shore and deep under water. However, the maintenance for subsea equipments are different from topside facilities, much longer time needed for retrieval of failed equipments and replacement of new one. Even though the condition monitoring has applied for many subsea equipments, the utilization ability of monitoring data and prognostics algorithms has not been deeply explored. In this paper, a subsea choke valve will be studied as a case, and the relevant prognostics issues are going to be discussed in this chapter.

4.1 Subsea choke valves introduction

As the choke valves used on topside, the subsea choke valves regulates the main flow from its corresponding wells into a common manifold. There are many suppliers of subsea chokes, namely, FMC Technologies, Master Flo, Cameron, etc. Different suppliers offers different types of subsea choke valves. While, according to Cameron website Cameron (2009), subsea chokes are typically used to:

- Start up and shut in subsea wells
- Balance pressures from different wells to a common manifold
- Reduce flow line pressures and costs

- Protect against reservoir collapse during startup
- Control flow rates to extend production life
- Protect subsea gate valves from high-pressure drops during startup and shutdown

The figure 4.1 is a simple sketch of angle style chokes. It is a single stage cage with an internal plug. For an overview of other typical used subsea chokes, see attachment A. And Figure 4.2 is a choke valve (P25 E BB 15000) from Master Flo.

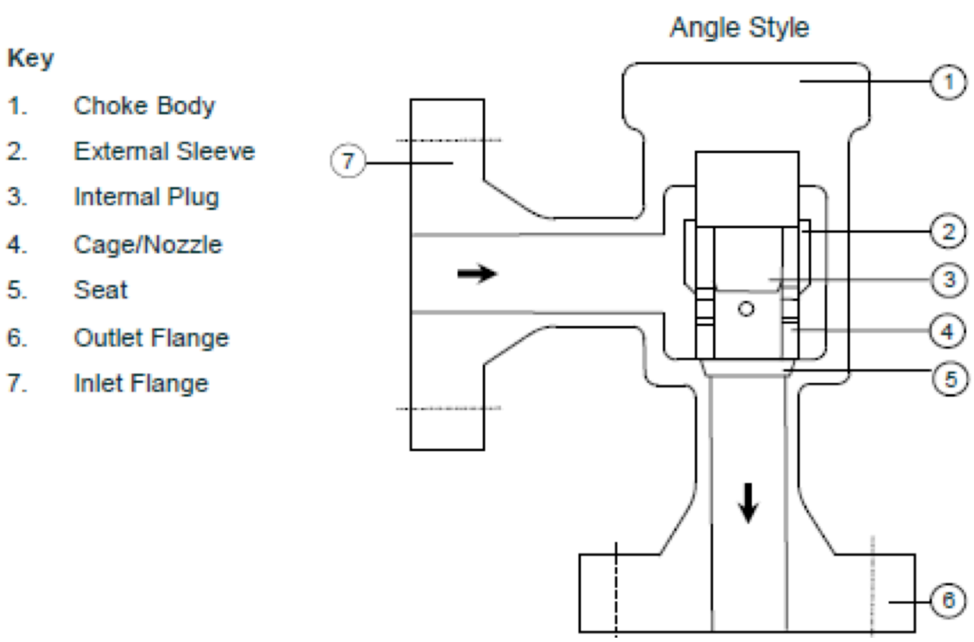

Figure 4.1: Single sketch of angle style choke valve, adapted from Master Flo

4.2 Choke valve erosion

Erosion is defined as the loss of original material due to solid particles impact on the material surface. If the particles are sand, then it is called sand erosion. The sand erosion potential increases as the flow velocity increases. Sand erosion is in general a major problem when it comes to choke valves. Sand production can not be avoided in the life cycle of the reservoir,

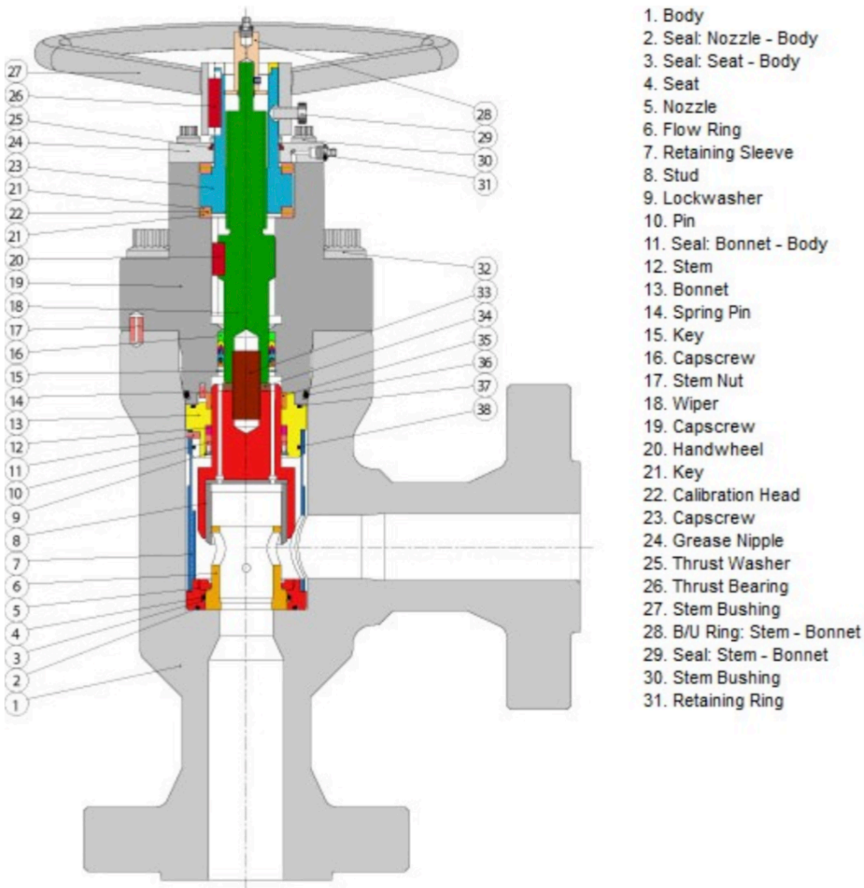

Figure 4.2: Choke valve P25 E BB 15000, adapted from Master Flo

especially in the late life phase when the pressure starts decreasing dramatically. For economic purpose downstream pressure at the choke valve is decreased to enhance the production rate, however at the same time more sand will pass through the choke valve and therefore increases the erosion rate of choke valve.

Many researches have been done so far within the choke erosion. Peri and Rogers (2007) has introduced how CFD can be used for modeling the erosion of choke valves. With the help of experiments or computational fluid dynamic modeling, many models for assessing the sand erosion rate are developed. Veritas (2007) has made a outline of most of the methods for piping systems. Sæther (2010) introduces some models for calculating choke valves erosion rate and also claims that C_v of valves is the best indicator on choke valve erosion.

Flow coefficient(C_v) of a device is a relative measure of its efficiency at allowing fluid flow. It describes the relationship between the pressure drop across an orifice, valve or other assembly and the corresponding flow rate. Therefore, the flow coefficient (C_v) is an important indicator of choke performance, and the difference between the actual and theoretical flow coefficient, $\delta_{C_v} = C_v^{ac} - C_v^{th}$, could be a good indicator of the valve erosion level.

4.3 Hybrid model for choke RUL estimation

In terms of choke erosion, directly observing the erosion level of the subsea choke valves is an unpractical issue, since they are located several hundred meters under the seawater, sometime even several thousand meters. Even for the retrievable subsea choke valve, it is also undesired from the economic point of view. From last section, the δC_v is considered to be a good choke valve degradation state indicator. If the value of indicator is obtained, Gamma process can be a practicable model for choke erosion prediction. In the next two sections the procedure of the application of hybrid model will be introduced in detail.

Before discussing the hybrid model for choke erosion, the issue of data set used in this paper is discussed here. Since the choke valves have been used for many decades in oil and gas industry and condition monitoring technologies are also developed many years ago, there should exist many historical records of chokes operational and environmental condition data. Unfortunately the data normally is kept by the operation companies as their secret database. So in this paper, the data used is generated artificially from Matlab and it is just used for model demonstration. The data set for 10 similar choke valves are listed in the appendix. The purpose is to show how the hybrid model is used for choke valve erosion prognostics and RUL calculation.

4.4 Visualization of the erosion indicator

4.4.1 Calculating δC_v

The theoretical flow coefficient C_v^{th} is always provided by the valve supplier, and is dependent on the valve type and valve opening (Stem travel shown in figure 4.3). An example is shown in the figure 4.3.

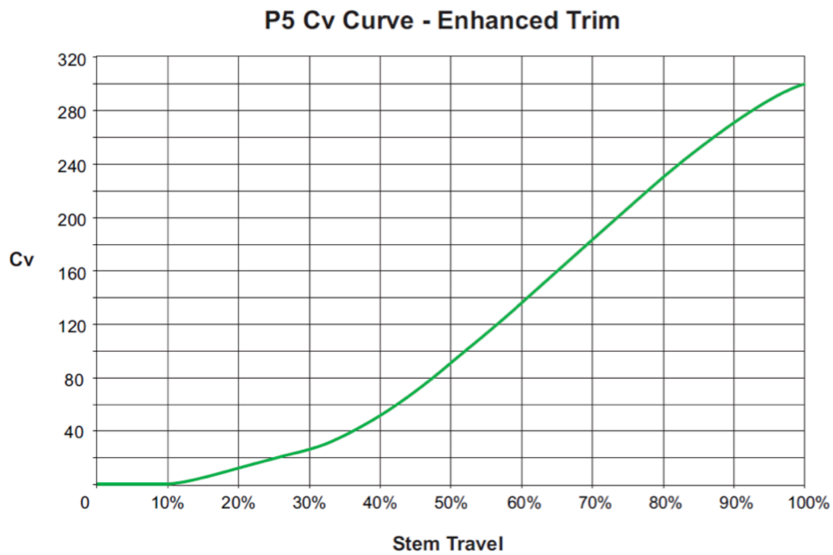

Figure 4.3: Theoretical C_v value of a choke valve from Master Flo Company

EMERSON (2010) has said Daniel Bernoulli has used principle of conservation of energy, and found the square of the fluid velocity is directly proportional to the pressure differential across the orifice and inversely proportional to the specific gravity of the fluid. And the equation can be written as

$$Q = C_v \sqrt{\Delta P / G} \tag{4.1}$$

Where:

Q= Capacity in gallons per minute of the mixture

C_v= Valve sizing coefficient

ΔP= Pressure differential in psi

G=Specific gravity of fluid

The standardized equation has been introduced in EMERSON (2010) and ISA-75.01.01-2007 (1989). The flow coefficient is derived as

$$C_v = \frac{q}{N_1 F_p \sqrt{\frac{P_1 - P_2}{G_f}}} \tag{4.2}$$

Where $q = q_g + q_w + q_o$, is the total volumetric flow rate of the mixture (kg/h). $N_1 = 0.865$, the value of N is shown in the Appendix B B.8. F_p is the so-called piping geometry factor and $P_1 - P_2$ is the pressure drop across the valve (bar), G_f is specific gravity of the mixture. And the specific gravity of the mixture can be calculated as

$$G_f = \frac{\left(\frac{f_g}{\rho_g * J^2} + \frac{f_w}{\rho_w} + \frac{f_o}{\rho_o}\right)^{-1}}{\rho_w} \tag{4.3}$$

Theoretically the relationship between the flow coefficient with other basic value type variables, such as pressure, temperature, and flow rate is built. Practically, the temperature, pressure, flow rate and the opening angle can be collected by high-tech sensors. With the development of the sensor technologies, it boosts the speed of implementing condition monitoring. The sensors for metering the temperature, pressure, and flow rate have already been used for oil and gas industry for many decades. Therefore on basis of on-line monitoring, the model based method for indicator visualization is to calculate the difference between the actual and theoretical flow coefficient, δC_v, can be derived as

$$\begin{aligned}\delta C_v &= C_v^{ac} - C_v^{th} \\ &= \frac{q}{N_1 F_p \sqrt{(P_1 - P_2)\left(\frac{f_g}{\rho_g * J^2} + \frac{f_w}{\rho_w} + \frac{f_o}{\rho_o}\right)^{-1} / \rho_w}} - C_v^{th}\end{aligned} \tag{4.4}$$

This calculation of δC_v can be carried out by Matlab directly, and the simple code is shown in figure 4.4 for demonstration.

4.4.2 Filtering of δC_v

Fitting in the actual everyday average value of the six on-line monitoring variables, the trend of outcome should be slightly increasing from the beginning, but it varies quite much, not always a monotonic increment. The main reasons are listed below:

a) The big sharp variance is due to the short valve opening variations;

b) The value of everyday flow rate of oil, gas, and water is not precise enough;

```
%generate some constant variables
syms rougas rouoil rouwater N6 Fp
rougas=a;
rouoil=b;
N1=0.865;
Fp=c;
% Generate a vector called Input for storing the value of dayly input and
% generatae an output vector as choke erosion level
Output=zeros(500)
for i=1:500
    % using input function to get the input values of mass flow rate of
    % gas, oil, water, and pressure drop, J, Cv_th.
    prompt='what is the dayly value Vector:'...
        'volumetric flow rate of gas oil water and pressure drop,J , Cv_th'
    Input=input(prompt);

    q_g(i)=input(1);
    q_o(i)=input(2);
    q_w(i)=Input(3);
    deltaP(i)=Input(4);
    J(i)=Input(5);
    q(i)=q_g(i)+q_o(i)+q_w(i);
    f_g(i)=q_g(i)/ q(i);
    f_o(i)=q_g(i)/ q(i);
    f_w(i)=q_g(i)/ q(i);
    Output(i)=(q_g(i)+q_o(i)+q_w(i))/(N1*Fp*sqrt(deltaP(i)...
      /(fg(i)/rougas*J(i)^(-2)+f_w(i)/rouwater+f_o(i)/rouoil)^(-1)...
      *rouwater)) - Cv_th;
    print(output(i))
end
```

Figure 4.4: Matlab code for calculate the δC_V

c) While, even though the sensor technologies are well developed at present, the value we get from sensors may still have some noises, which makes the pressure drop between the choke are little noisy, as well as the temperature, and the opening angle value.

However, the prerequisite of gamma process is that the δC_v should be a monotonically increasing process. So more works should be done for outcome data δC_v. There are many common methods exists for data filtering and smoothing, such as moving average, Savitzky-Golay filters, and local regression with and without weights and robustness (lowess, loess, rlowess and rloess). Moving average is widely used for simple data smoothing. A moving average filter smooths data by replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low-pass filtering with the response of the smoothing given by the difference equation:

$$y_s(i) = \frac{1}{2N+1}(y(i+N) + y(i+N-1) + ... + y(i-N)) \tag{4.5}$$

where $y_s(i)$is the smoothed value for the ith data point, $2N+1$ is the span.

After the moving average smoothing, the next step is to use moving maxima filtering to get a monotonic trend. Finally the monotone data sets are obtained and can be used for prognostics. The figure 4.5 shows the plot of the original output data (red line), smoothed data (blue line) and the final monotone data (green line). And the Matlab code is shown in figure 4.6

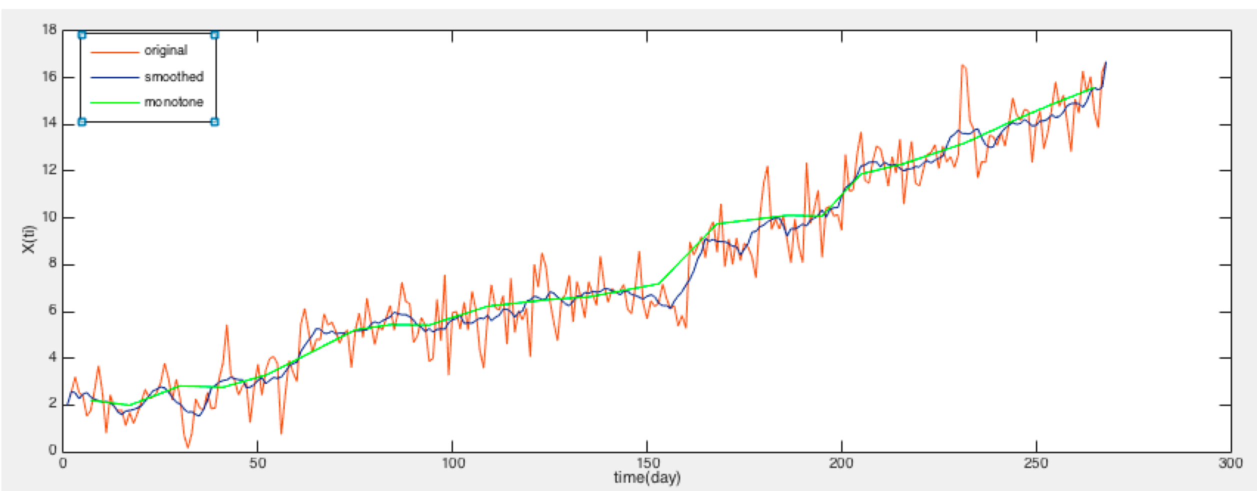

Figure 4.5: The plot of three types of data

4.4.3 Building ANNs model

Since ANNs is a good method for modeling the nonlinear relationship between input and output, ANNs will be used for modeling the relationship between the erosion level and the choke

```
load U;
Y=smooth(U,8,'rloess');
plot(1:268,U);
hold on;
plot(Y);
hold on;
[pks,locs] = findpeaks(Y,'MinPeakDistance',5);
plot(locs,pks)
```

Figure 4.6: Matlab code for data processing

operational condition such as the pressure and flow rate. Now one feed-forward neural network (FFNN) model has built with six inputs and one output. The input in the training data set is the original data collected form sensors, namely, upstream and downstream pressure drops, the valve opening angle, and the daily oil, gas and water flow rate. The output data is the final processed values, X_{t_i}.

And the feed-forward neural network (FFNN) model of the choke erosion is built using a toolbox in Matlab. The ANNs consists of 5 inputs and one hidden layer with 10, 15 neurons respectively and one output elements. The data used is generated manually, and it is a matrix of $5*758$ (Choke A and B monitoring data), and the results is shown in Appendix B. Due to lacking of real data, the accuracy is not good enough, but the objective is just demonstration.

4.5 Gamma process parameter estimation

4.5.1 Maximum likelihood method

Figure 4.7 is a plot of the erosion level at each day within the life cycle of choke A obtained by the ANNs model. As shown in the figure 4.7, until 268 days, the erosion level $X_{t_{268}}$ of this choke reached the threshold, which is always estimated by the expert. Once the reliable processed outcome , the value of X_{t_i}, is computed, gamma process with shape parameter $\lambda(t)$, and scale parameter u will be used for erosion prediction.

The increment at time t_i is $d_i = X(t_i) - X(t_{i-1})$ and the shape function is $ct_i^b - ct_{i-1}^b$, b is a known constant, and the scale parameter is u. So the increment density function can be derived

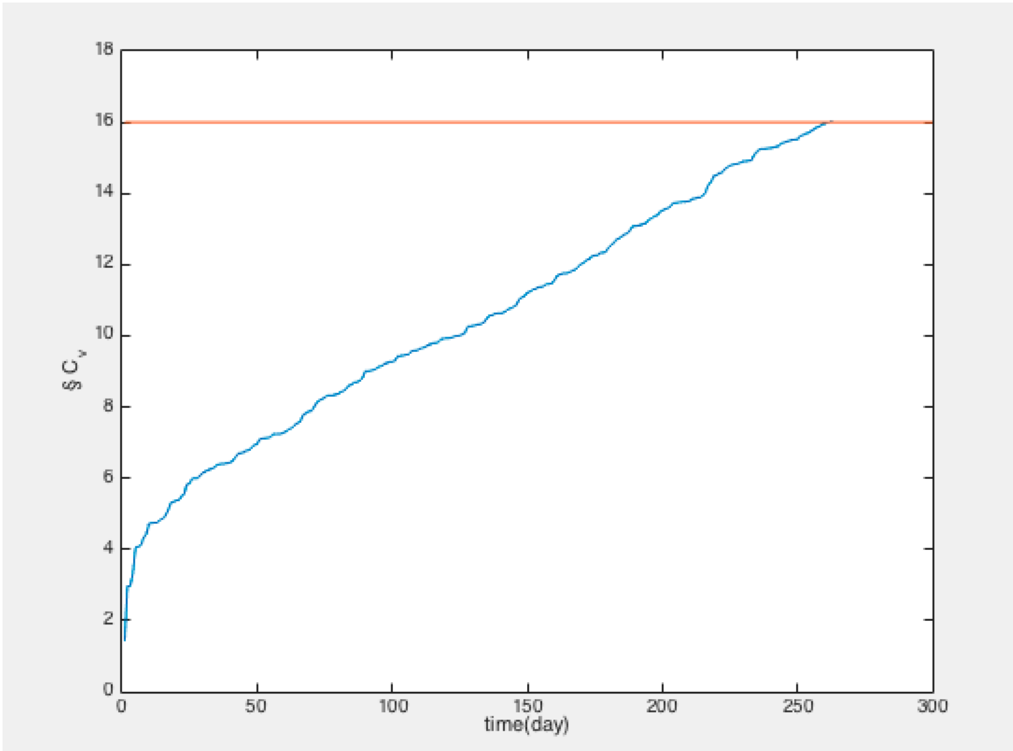

Figure 4.7: The plot of the trend of the Choke A erosion indicator

as

$$f_{X(t_i)-X(t_{i-1})}(x) = \frac{u^{ct_i^b - ct_{i-1}^b}}{\Gamma(ct_i^b - ct_{i-1}^b)} x^{ct_i^b - ct_{i-1}^b - 1} e^{-ux} = Ga\left(x|ct_i^b - ct_{i-1}^b, u\right) \tag{4.6}$$

And the likelihood function is

$$\begin{aligned} L(d_1, d_2, ..., d_n|c, u) &= \prod_{i=1}^{268} f_{X(t_i)-X(t_{i-1})}(d_i) \\ &= \prod_{i=1}^{268} \frac{u^{c(t_i^b - t_{i-1}^b)}}{\Gamma[c(t_i^b - t_{i-1}^b)]} d_i^{c(t_i^b - t_{i-1}^b)} e^{-ud_i} \end{aligned} \tag{4.7}$$

The cumulative amounts of erosion at last inspection time t_{268} is measured as $x_{268} = 16.1425$. According to expected value $E(X(t_n)) = x_n$, the estimated value of scale parameter can be derived as

$$\hat{u} = \frac{\hat{c} t_n^b}{x_n} = \frac{\hat{c} 268^b}{16.1425} \tag{4.8}$$

Taking logarithm of the likelihood function, the log-likelihood function is

$$\begin{aligned}
&\frac{\partial}{\partial c} logL(d_1, d_2, ..., d_n|c,u) \\
&= \sum_{i=1}^{n} \frac{\partial}{\partial c} \left\{ c[t_i^b - t_{i-1}^b] log\left(\frac{ct_n^b}{x_n}\right) - log\Gamma(c[t_i^b - t_{i-1}^b]) + \left(c[t_i^b - t_{i-1}^b] - 1\right) log\delta_i - \frac{ct_n^b}{x_n}\delta_i \right\} \\
&= \sum_{i=1}^{n} \left\{ [t_i^b - t_{i-1}^b] \left[log\left(\frac{ct_n^b}{x_n}\right) + 1 - \psi(c[t_i^b - t_{i-1}^b]) + log\delta_i \right] - \frac{t_n^b}{x_n}\delta_i \right\} \\
&= t_n^b log\left(\frac{ct_n^b}{x_n}\right) + \sum_{i=1}^{n} [t_i^b - t_{i-1}^b] \left\{ log\delta_i - \psi(c[t_i^b - t_{i-1}^b]) \right\} \\
&= 0
\end{aligned} \tag{4.9}$$

Where the function $\psi(a)$ is the derivative of the logarithm of the gamma function:

$$\psi(a) = \frac{\Gamma'(a)}{\Gamma(a)} = \frac{\partial log\Gamma(a)}{\partial a} \tag{4.10}$$

for $a > 0$. Summarizing the maximum likelihood estimation, we can get

$$\hat{u} = \frac{\hat{c}268^b}{16.1425}, \sum_{i=1}^{268} [t_i^b - t_{i-1}^b] \left\{ \psi(c[t_i^b - t_{i-1}^b]) - log\delta_i \right\} = 268^b log\left(\frac{c268^b}{16.1425}\right) \tag{4.11}$$

The parameter b is assumed to be 1, and the other two parameters c and β are estimated by Matlab, and the code is shown below in figure 4.8. The result from the maximum likelihood estimation is listed as formula 4.12 and the figure of estimated expected erosion level is shown in figure 4.9, and some other figures with different b values are shown in the Appendix. In addition, for Choke B, the results are shown in the Appendix.

$$\hat{c} = 0.8487, \hat{u} = 14.0902 \tag{4.12}$$

As shown in figure 4.9, the red line is actual δC_v and the blue line is the plot of estimated value. The erosion level is overestimated when $t < 160$, while it is underestimated by the expected value from the gamma proces when $t > 160$. The same happens with the other b values ($b \neq 1$), even though they do not represent linear increments. The solution for this problem is to use Bayesian method for updating estimate parameters to reach a more precise estimation.

```
% Originally we get the raw data everyday Output(i), and after processing
% (smoothing,filtering) we get the data M(i), the cummulative erosion level
%First we calculate the increments during each interval.
for i=1:267
X(i)=M(i+1)-M(i);
end
%Then we use formula 4.12 to estimate the parameter c
syms g b tn xn c
g=0;
tn=268;
xn=16.1425;
b=1;
for i=1:267
g=g+((i+1)^b-i^b)*(psi(c*((i+1)^b-i^b))-log(X(i)));
end
eqn=268^b*log(c*268^b/16.1425)-g==0;
solc=solve(eqn,c);
%here we should use code below to get the variable c
ezplot(g, 0, 2)
hold on
ezplot(268^b*log(c*268^b/16.1425), 0, 2)
hold off
vpasolve(g == 268^b*log(c*268^b/16.1425), c, [0 2])
syms u
u=c*268^b/16.1425
```

Figure 4.8: Matlab code for estimate c and u

4.5.2 Bayesian method for updating u

As discussed above, using a fixed estimated parameter value is sometimes troublesome and can not produce a precise prediction. Here, Bayesian method is proposed for estimating the scale parameter since it is always assumed to be constant in gamma process. It is not reasonable to have a constant parameter since there always exists some variance, even though some components may be similar. While, Bayesian method can exactly solve this problem.

In general, Bayes theorem can be written as

$$f(\theta|x) = \frac{f(\theta)\pi(x|\theta)}{\int \pi(\theta)} \tag{4.13}$$

According to van Noortwijk (2009), the family of gamma distribution is a conjugate family with respect to the gamma likelihood function with unknown scale parameter, as both prior and

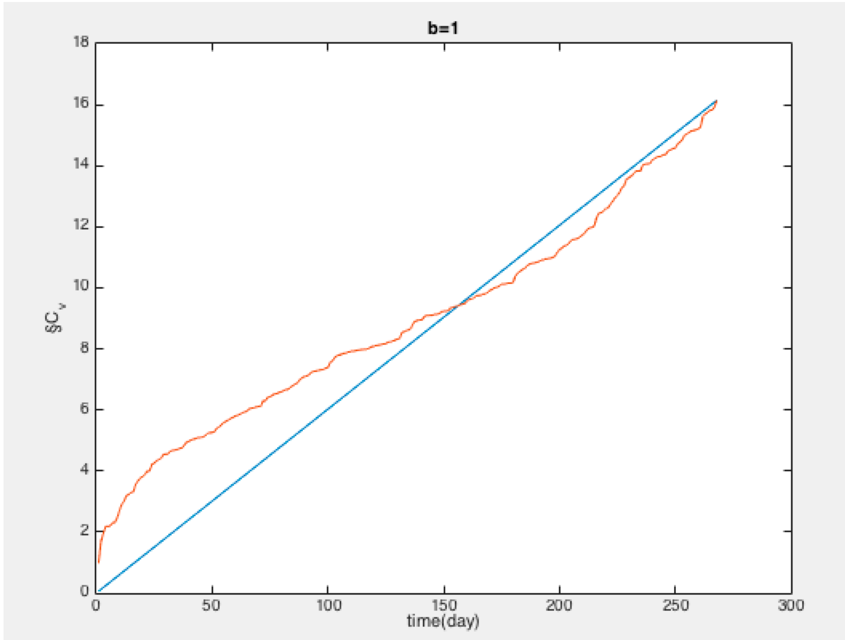

Figure 4.9: Estimated expected δC_v when b=1

posterior distribution belong to the family of gamma distributions. Therefore, scale parameter u is assumed to be a gamma distribution with shape parameter α and scale parameter β. The prior distribution of scale parameter u can be written as

$$f(u|\alpha,\beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} u^{\alpha-1} exp(-u\beta) \tag{4.14}$$

The parameters α and β is either from expert judgment, or derived from parameter estimation. Here assuming that for the historical data of similar valves, maximum likelihood has been used for estimating c and u, and then the expected value of u and variance of u can be easily derived. According to the property of gamma distribution, $E(u) = \frac{\alpha}{\beta}$ and $V(u) = \frac{\alpha}{\beta^2}$, the value of α and β can be calculated.

And the posterior distribution can be derived as

$$
\begin{aligned}
& f(u|d_1,d_2,...,d_n) = f(u|\alpha,\beta)L(d_1,d_2,...,d_n) \\
& = \frac{\beta^\alpha}{\Gamma(\alpha)} u^{\alpha-1} exp(-u\beta) \prod_{i=1}^{n} \frac{u^{c(t_i^b - t_{i-1}^b)}}{\Gamma[c(t_i^b - t_{i-1}^b)]} d_i^{c(t_i^b - t_{i-1}^b)} e^{-ud_i} \\
& = Ga(u|\alpha + ct_n^b, \beta + x_n) \times \left(\frac{1}{\beta + x_n}\right)^{\alpha + ct_n^b} \frac{\beta^\alpha \Gamma(\alpha + ct_n^b)}{\Gamma(\alpha)} \prod_{i=1}^{n} \frac{d_i{}^{c(t_i^b - t_{i-1}^b)}}{\Gamma(c(t_i^b - t_{i-1}^b))} \\
& \propto Ga(u|\alpha + ct_n^b, \beta + x_n)
\end{aligned}
\tag{4.15}
$$

Where c is an known variable, which is estimated by maximum likelihood function. As shown in the formula 4.15, the posterior distribution of u is also a gamma distribution with shape parameter $\alpha + ct_n^b$ and scale parameter $\beta + x_n$.

As discussed in last section, the parameter b is assumed to be 1, and other parameters c and u are estimated by maximum likelihood method. For parameter u, the expected value is 14, and the variance is 9. To make the prediction more precise, the Bayesian method will be applied for updating parameter u. so the prior distribution of u is $Ga(u|\alpha = 1.6, \beta = 21.7)$, once a new X_i is collected, then derive the posterior distribution. The Beyes esimate is given by the mean in this distribution of u.

$$\hat{u} = \frac{\alpha + ct_i}{\beta + x_i} = \frac{21.7 + ct_i}{1.6 + x_i} \tag{4.16}$$

After applying Bayes method, the prediction is shown in the figure 4.10. From the plot, it shows that as more data collected for the choke A, more precise the prediction will be.

4.6 Residual useful life Prediction

For choke A, by setting the erosion threshold, $L = 16$, and $b = 1, c = 0.85, u = 14$ the cumulative lifetime distribution can be obtained as

$$F(t) = Pr(T \leqslant t) = Pr(X \geqslant L) = \int_{16}^{\infty} \frac{14^{0.85t}}{\Gamma(0.85t)} x^{0.85t-1} e^{-14x} dx = \frac{\Gamma(0.85t, 14 * 16)}{\Gamma(0.85t)} \tag{4.17}$$

Plot the $F(t)$ in Matlab, the plot is with some error, since the data is generated randomly. And also because the estimation of parameters is at time $t = 0$ without Bayesian method is not

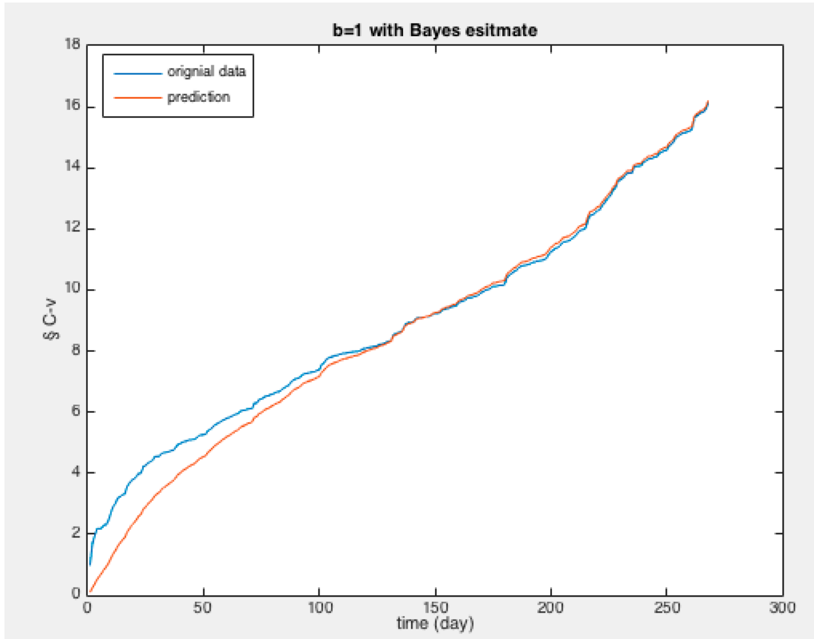

Figure 4.10: Estimated expected δC_v when b=1 with Bayesian method

accurate. However when $t = 100$, with Bayesian estimation of scale parameter, $u = 2.97$, and the plot of $F(t|X_{t_{100}})$ is shown below in figure 4.11 the cumulative distribution function of the RUL is derives as

$$\begin{aligned}
&F(t|X_{100}) = Pr(T \leqslant t|X_{100} = 7.23)\\
&= Pr(X_t \geqslant L)\\
&= \int_{16}^{\infty} \frac{2.97^{0.85t}}{\Gamma(0.85t)} x^{0.85t-1} e^{-2.97x} dx\\
&= \frac{\Gamma(0.85t, 2.97*16)}{\Gamma(0.85t)}
\end{aligned} \tag{4.18}$$

The residual useful life distribution at time $t = 100days$ is calculated as equation4.19 and the plot of the cumulative distribution of RUL at $t = 100$ is shown in figure 4.12

$$\begin{aligned}
&F_{RUL(t_{100})}(h) = Pr(RUL(t_{100}) < h)\\
&= Pr(X_{t_{100+h}} > L|X_{t_{100}} < L, X_{t_100} = 7.23)\\
&= Pr(X_{t_{100+h}} - X_{t_{100}} \geqslant L - x_{t_{100}}|X_{t_{100}} < L)\\
&= \frac{\int_{L-x_{t_j}}^{\infty} Ga\left(v|ch, \frac{\alpha+ct_j}{\beta+x_{t_j}}\right) dv}{\int_0^L Ga\left(v|ct_j, \frac{\alpha+ct_j}{\beta+x_{t_j}}\right) dv}
\end{aligned} \tag{4.19}$$

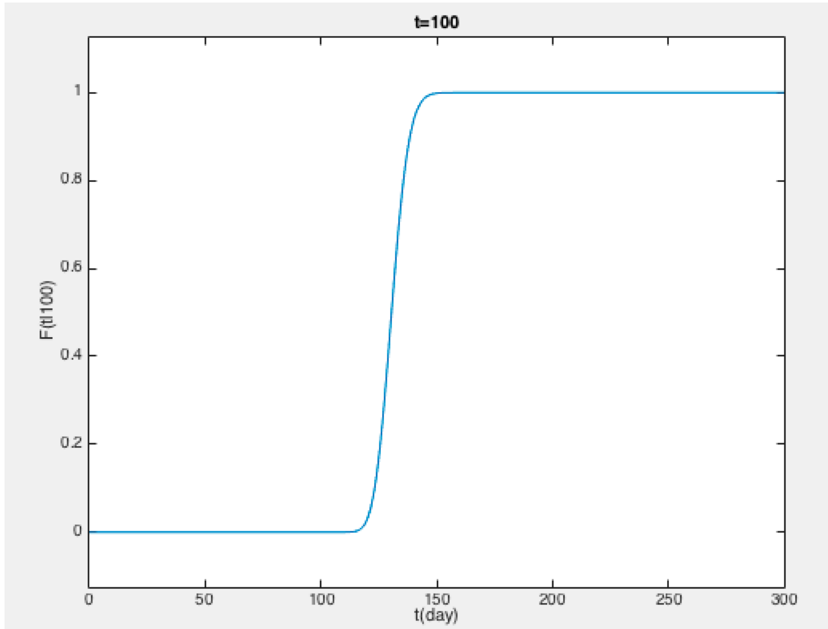

Figure 4.11: The cumulative F(t|100)

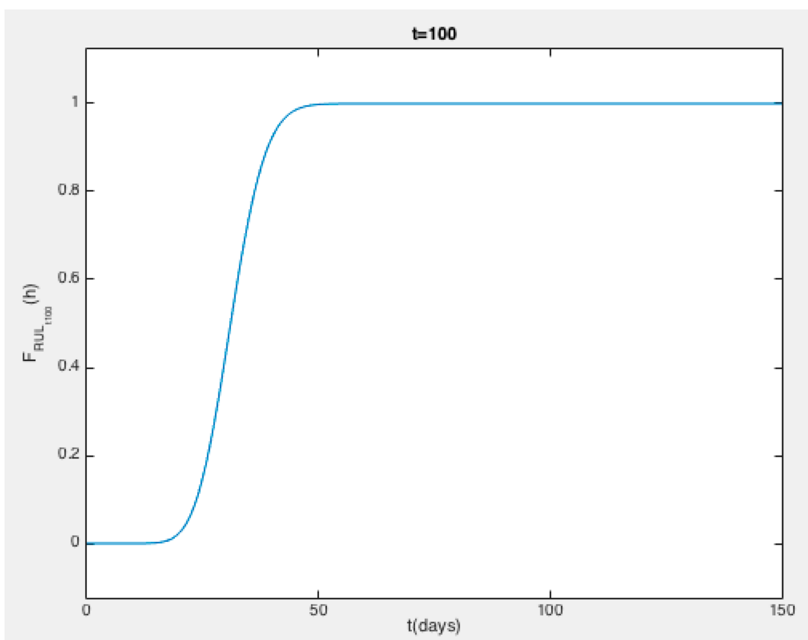

Figure 4.12: The cumulative F(t|100)

The RUL cumulative density function is the output of the prognostic algorithm and it describes the distribution in respect of likely residual time of equipment. Seen from figure 4.11, at time $t = 100 days$ the residual life estimation is generated. If the acceptable probability of failure is 0.1, which defines the acceptable risk level, the latest time when the maintenance must to be carried out is about 30 days in the future. Considering other aspects such as the time length needed for maintenance (MTTR), the availability of spare parts together with the RUL, the optimal maintenance schedule will be decided.

Chapter 5

Summary and recommendations for further work

5.1 Summary and conclusions

The thesis has presented the main content of prognostics and health management and its procedure. It summarized the relevant theory and techniques within each steps, namely, data acquisition and processing, and diagnostics and prognostics which is the foundation of decision making. In addition, a systematic and comprehensive review of different methods and models for diagnostics and prognostics has been presented, such as the statistical control method for diagnostics and the the conventional reliability method, artificial intelligence method, and stochastic methods and model based method for prognostics.

After the review, the problem of degradation prognostics is discussed. Various research has done on degradation and gamma process is approved to be a well known stochastic method for solving degradation problems. Whilst the problem of the unobservable degradation indicator has not been deeply studied. In this paper, a proposed hybrid model is introduced and developed to deal with the limitation of applying Gamma process into the degradation prognostics. The hybrid model first trains a ANNs model to use the indirect monitored variables to obtain a monotonically increasing degradation indicator, and the data processing tasks need to be done before the ANNs training. And the next step is to apply Gamma process to the degradation prognostics and calculate the residual useful life. The gamma process parameter estimation is improved by applying bayesian method for updating the scale parameter. The main reason for developing the hybrid model instead of using a single one is to take advantage of the ANNs powerful nonlinear regression ability and the well-known ability of modeling degradation by Gamma process.

Subsea choke valve erosion is studied as a case. The flow coefficient is selected as the degradation indicator. The results from the hybrid prognostic model, the distribution of RUL is one of the vital and supportive information for scheduling maintenance tasks such replacement of valves. This proposed hybrid model can not only be applied to subsea valves erosion prognostics, but also can be applied to other equipment degradation prognostics problem. For other equipment degradation, each time applying this model, new relationship with the indicator and relevant covariates should be investigated for the indicator visualization.

5.2 Discussion

The fist part of the hybrid model is degradation visualization, and the method varies. The indicator of degradation may be obtained from only a single measured variable or some variables together. For example, the bearing degradation can be obtained by the value of the amplitude of the corresponding frequency based on the motor vibration. The key is to find the right indicator that can represent the current condition of the equipment, and the relationship between the indicator and its relevant measurable covariates.

5.3 Recommendations for further work

You should give recommendations to possible extensions to your work. The recommendations should be as specific as possible, preferably with an objective and an indication of a possible approach.

The recommendations may be classified as:

- Due to the time limitation and lacking of real data, the hybrid model sensitivity has not been studied, especially for the ANNs model. The indicator visualization is the foundation of the prognostics by applying gamma process. The issue such as the data smoothing method, the input numbers of ANNs model should be studied further in the future research.

- Electrical equipments are more commonly used in industries, for example, Subsea industry is focus on developing all electrical control systems. However, in this paper more focus is put on machinery, therefore, the models for electronics deterioration prognostics should be paid more attention.

- The subsystems or the components health condition assessment and their fault prognostics are the main focus at present, however, it is also very important to get the health status at the the system level.

Appendix A

Acronyms

PM Preventive maintenance

CM Corrective maintenance

CBM Condition-based maintenance

PHM Prognostics and health management

CM Condition monitoring

SPC Statistical process control

PCA Principal component analysis

PLS Partial least squares

MTBF Mean time between failure

TTF Time to failure

AI Artificail intelligent

SVM Support vector machines

ANNs Artificial neural networks

RNN Recurrent neural network

FFNN Feed-forward neural network

RUL Residual useful life

Var Variance

COV Coefficient of variance

MLE Maximum likelihood estimation

Appendix B

B.1 ANNs

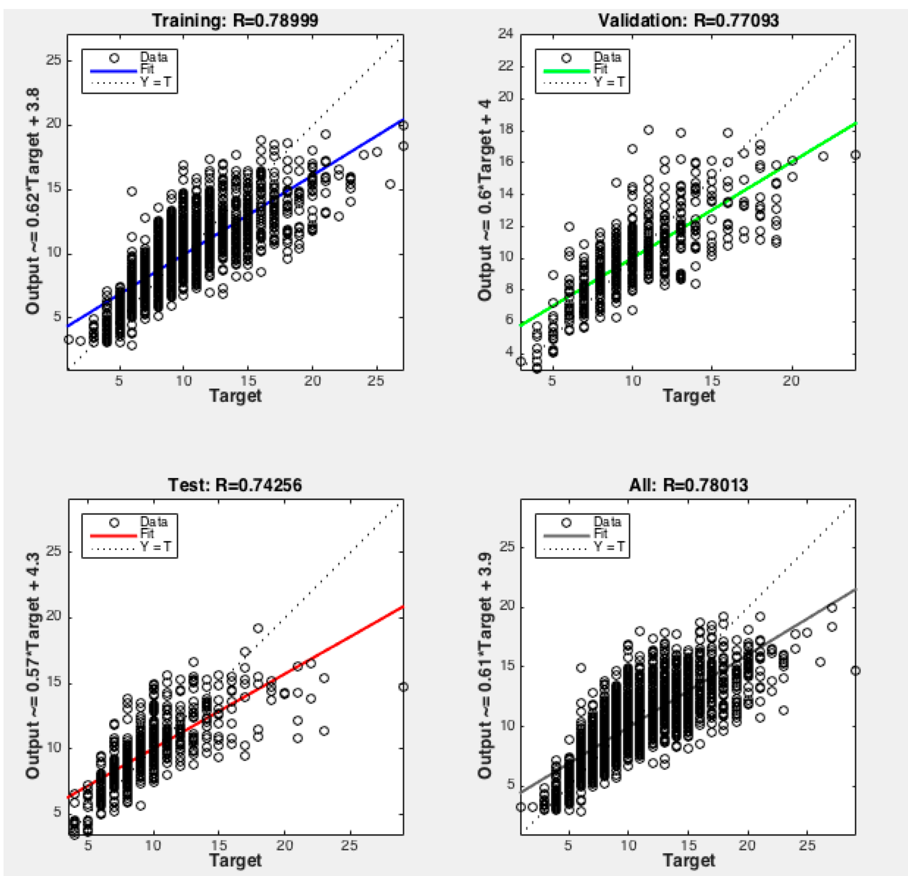

Figure B.1: The simulation results of ANNs fitting when there are 10 neurons in hidden layer

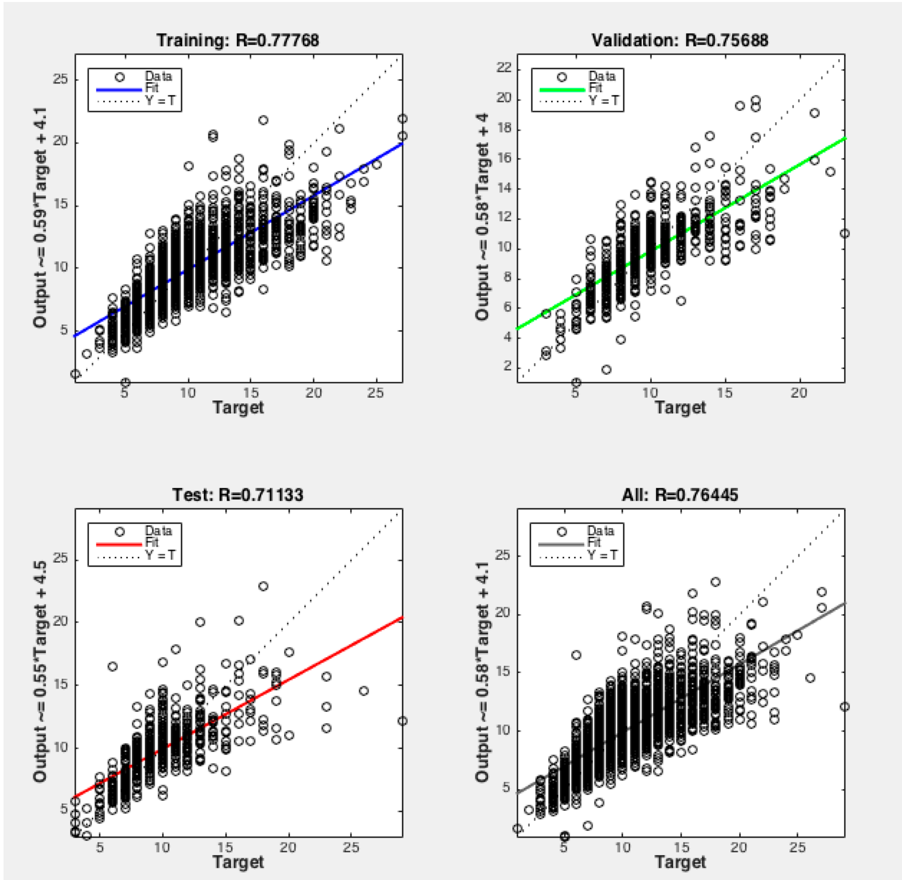

Figure B.2: The simulation results of ANNs fitting when there are 15 neurons in hidden layer

B.2 Choke A

For choke A, using maximum likelihood estimation for parameter c and u, when assuming $b = 0.5$ and the results is $\hat{c} = 23.15$, $\hat{u} = 23.47$; when assuming $b = 1.5$, the estimated parameter $\hat{c} = 2.83$, $\hat{u} = 0.8$. The following two figures **??** and B.5 are the plots of the estimated expected δC_v

B.3 Choke B

For choke B, the plot of the degradation trend that obtained from the ANNs model is shown in figureB.6.

The maximum likelihood estimation code is shown below in figure B.7. And the results of the estimated parameters are $\hat{c} = 0.74$, $\hat{u} = 12.28$ when $b = 1$ and $\hat{c} = 0.035$, $\hat{u} = 9.51$ when $b = 1.5$.

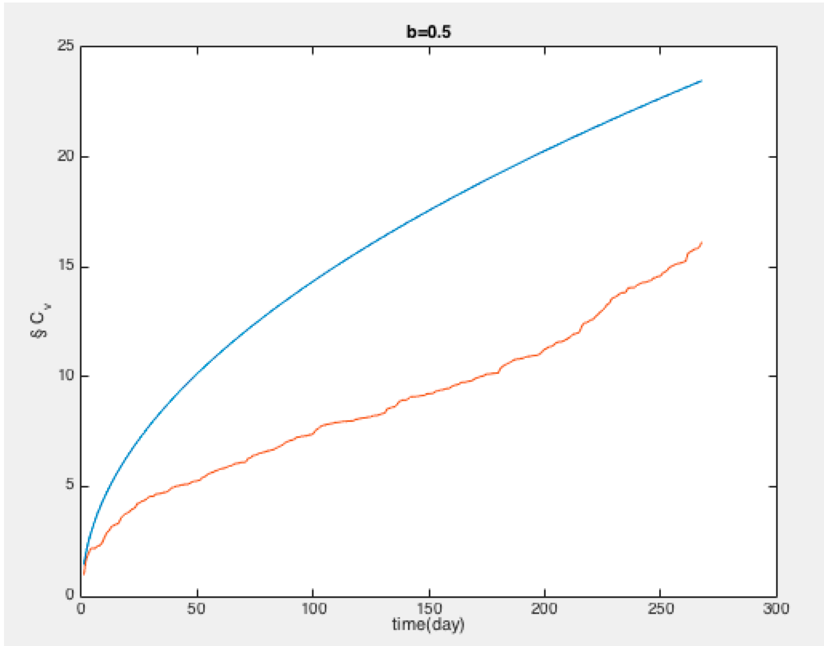

Figure B.3: Estimated expected δC_v when b=0.5 without Bayesian method

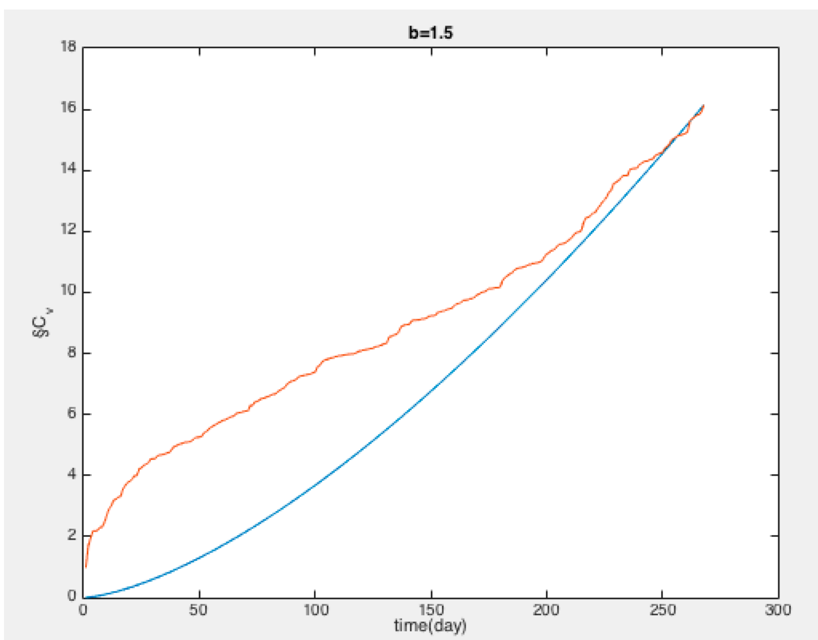

Figure B.4: Estimated expected δC_v when b=1.5 without Bayesian method

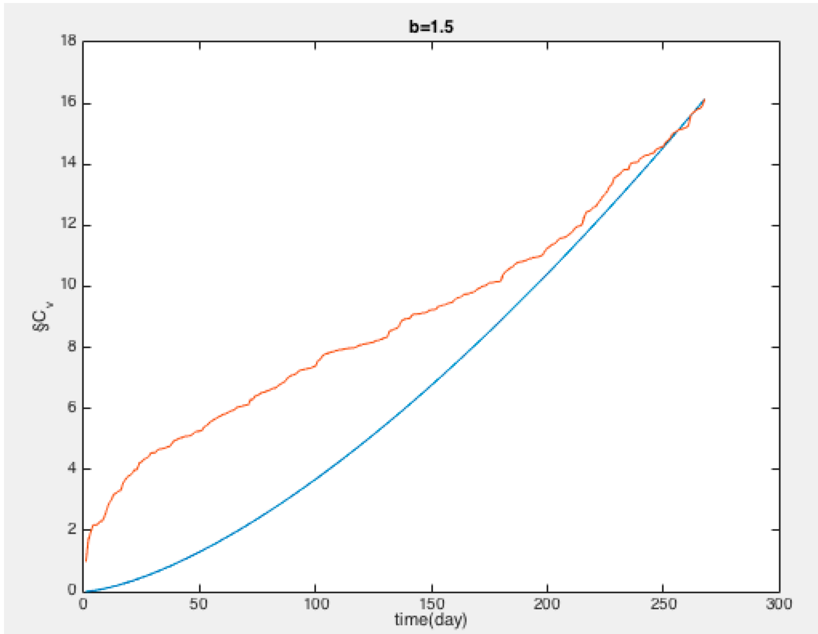

Figure B.5: Estimated expected δC_v when b=2 without Bayesian method

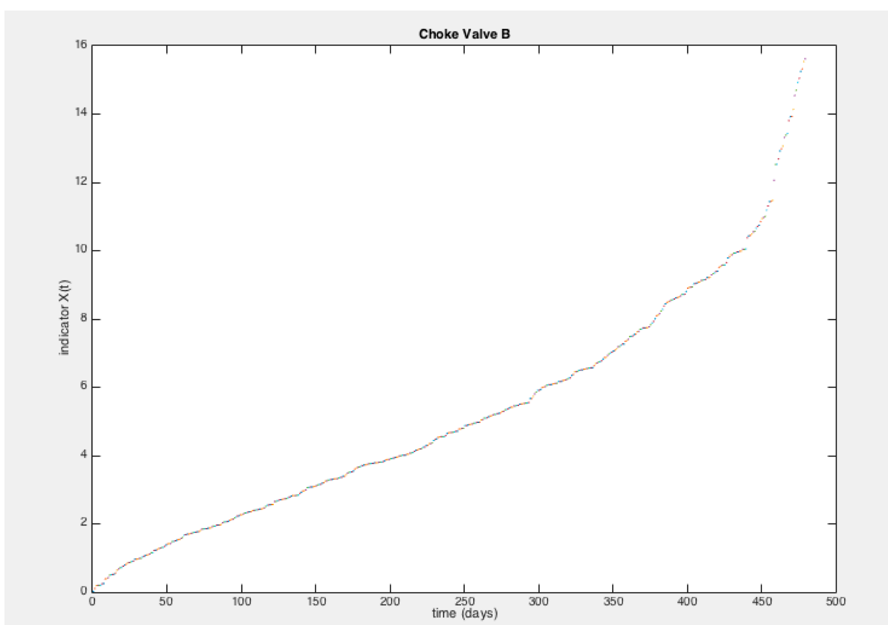

Figure B.6: The plot of the choke B erosion indicator

```
% Originally we get the raw data everyday Output(i), and after processing
% (smoothing,filtering) we get the data M(i), the cummulative erosion level
%First we calculate the increments during each interval.
for i=1:480
X(i)=M(i+1)-M(i);
end
%Then we use formula 4.12 to estimate the parameter c
syms g b tn xn c
g=0;
tn=481;
xn=15.9999;
b=1;
for i=1:480
g=g+((i+1)^b-i^b)*(psi(c*((i+1)^b-i^b))-log(X(i)));
end
eqn=tn^b*log(c*tn^b/xn)-g==0;
solc=solve(eqn,c);
%here we should use code below to get the variable c
ezplot(g, 0, 2)
hold on
ezplot(tn^b*log(c*tn^b/xn), 0, 2)
hold off
vpasolve(g == tn^b*log(c*tn^b/xn), c, [0 2])
syms u
u=c*268^b/16.1425
```

Figure B.7: Matlab code for parameter estimation of choke B

Constant	Flow coefficient C		Formulae unit						
	K_v	C_v	W	Q	$P, \Delta P$	ρ	T	d, D	ν
N_1	1×10^{-1} 1	8.65×10^{-2} 8.65×10^{-1} 1	– – –	m^3/h m^3/h gpm	kPa bar psia		– – –	– – –	– – –
N_2	1.60×10^{-3}	2.14×10^{-3} 8.90×10^{2}	– –	– –	– –	– –	– –	mm in	– –
N_4	7.07×10^{-2}	7.60×10^{-2} 1.73×10^{4} 2.153×10^{3}	– – –	m^3/h gpm scfh	– – –	– – –	– – –	– – –	m^2/s cS cS
N_5	1.80×10^{-3}	2.41×10^{-3} 1.00×10^{3}	– –	– –	– –	– –	– –	mm in	– –
N_6	3.16 3.16×10^{1}	2.73 2.73×10^{1} 6.33×10^{1}	kg/h kg/h lbm/h	– – –	kPa bar psia	kg/m^3 kg/m^3 lbm/ft^3	– – –	– – –	– – –
N_7 (t = 15.6°C)	4.82 4.82×10^{2}	4.17 4.17×10^{2} 1.36×10^{3}	– – –	m^3/h m^3/h scfh	kPa bar psia	– – –	–K –K –R	– – –	– – –
N_8	1.10 1.10×10^{2}	9.48×10^{-1} 9.48×10^{1} 1.93×10^{1}	kg/h kg/h lbm/h	– – –	kPa bar psia	– – –	K K R	– – –	– – –
N_9 (t = 0°C)	2.46×10^{1} 2.46×10^{3}	2.12×10^{1} 2.12×10^{3} 6.94×10^{3}	– – –	m^3/h m^3/h scfh	kPa bar psia	– – –	K K R	– – –	– – –
N_9 (t_s = 15°C)	2.60×10^{1} 2.60×10^{3}	2.25×10^{1} 2.25×10^{3} 7.32×10^{3}	– – –	m^3/h m^3/h scfh	kPa bar psia	– – –	K K R	– – –	– – –
N_{18}	8.65×10^{-1}	1.00 6.45×10^{2}	– –	– –	– –	– –	– –	mm in	– –
N_{19}	2.5	2.3 9.06×10^{-2}	– –	– –	– –	– –	– –	mm in	– –
N_{22} (t_s = 0°C)	1.73×10^{1} 1.73×10^{3}	1.50×10^{1} 1.50×10^{3} 4.92×10^{3}	– – –	m^3/h m^3/h scfh	kPa bar psia	– – –	K K R	– – –	– – –
N_{22} (t_s = 15°C)	1.84×10^{1} 1.84×10^{3}	1.59×10^{1} 1.59×10^{3} 5.20×10^{3}	– – –	m^3/h m^3/h scfh	kPa bar psia	– – –	K K R	– – –	– – –
N_{27} (t_s = 0°C)	7.75×10^{-1} 7.75×101	6.70×10^{-1} $6.70 \times 10^{+1}$ 1.37×10^{1}	kg/h kg/h lbm/h	– – –	kPa bar psia	– – –	K K R	– – –	– – –
N_{32}	1.40×10^{2}	1.27×10^{2} 1.70×10^{1}	– –	– –	– –	– –	– –	mm in	– –

NOTE Use of the numerical constants provided in this table together with the practical metric and US units specified in the table will yield flow coefficients in the units in which they are defined.

Figure B.8: The value of N, adapted from ISA-75.01.01-2007 (1989)

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Language Skills

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Education

- 2013.08 - 2015.07 Norwegian University of Science and Technology
  RAMS Engineering (Reliability, Availability, Maintainability and Safety) GPA: B

- 2008.09 - 2012.07 China University of Geosciences (Beijing)
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Computer Skills

- Visual Basic, C Language, Python
- Minitab, SMILE, CARA Fault Tree, RCM++
- AutoCAD, PyroSim, Eclipse (basic), PLC (basic)

Experience

- 2015.01-2015.06 Norwegian University of Science and Technology
  Title: Student Assistant (RAMS Engineering and Management Course)
- 2013.01-2015.06 Tsinghua Urban Planning and Design Institute
  Title: Fire protection design engineer
  -Proficiency in using PyroSim (Fluid Dynamics Simulation) Software
  -Analysed the fire development, smoke and heat transmission
  -Technically support for developing fire protection strategy
  -Involved in projects Kunming Historical Block Fire Safety Risks Analysis, and Fire Prevention and Control Planning of Gu Lei Port Economic Development Zone

Hobbies and Other Activities

- 2015.02 - 2015.02 Volunteer of introducing Chinese Culture in Trondheim
- 2014.10 - 2014.10 Your Extreme 2014 held by Kongsberg
- 2014.08 - 2014.08 Volunteer of Coralua Trondheim International Choir Festival
- 2009.05 - 2014.10 Volunteer of Chinese 60th anniversary celebration parade phalanx
- 2008.09 - 2010.07 President of Class 024081
  -Organised more than 25 collective activities, including two New Year Galas.
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- 2008.09 - 2009.07 Member of University Modern Drama Troupe

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