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Integrated Diagnosis and Prognosis Model for High Pressure LNG Pump

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Abstract

In condition-based maintenance (CBM), effective diagnostics and prognostics are essential tools for maintenance engineers to identify imminent fault and to predict the remaining useful life before the components finally fail. This enables remedial actions to be taken in advance and reschedules production if necessary. This paper presents a technique for accurate assessment of the remnant life of machines based on historical failure knowledge embedded in the closed loop diagnostic and prognostic system. The technique uses the Support Vector Machine (SVM) classifier for both fault diagnosis and evaluation of health stages of machine degradation. To validate the feasibility of the proposed model, the five different level data of typical four faults from High Pressure Liquefied Natural Gas (HP-LNG) pumps were used for multi-class fault diagnosis. In addition, two sets of impeller-rub data were analysed and employed to predict the remnant life of pump based on estimation of health state. The results obtained were very encouraging and showed that the proposed prognosis system has the potential to be used as an estimation tool for machine remnant life prediction in real life industrial applications.

Key words: Diagnosis, Prognosis, Support Vector Machine(SVM), LNG pump

1. Introduction

The ability to accurately predict the remaining useful life of a machine system is critical for its operation and can also be used to improve productivity and enhance system safety. In condition-based maintenance, maintenance is usually performed based on an assessment or prediction of the machine health instead of its service time, which leads to intended usage of the machine, reduced down time and enhanced operation safety. An effective prognostics program will provide lead time for maintenance engineers to schedule a repair and to acquire replacement components before catastrophic failures occur.

Although today's diagnostic engineers have significant knowledge and experience about machine failure and health states by continuously monitoring and analysing of machine condition in industry, well understood systematic methodologies and supporting systems on how to predict machine remnant life are still not available in commercial scale. This task still relies on human expert knowledge and experience. Therefore, there is an urgent need to continuously develop and improve prognostic models which can be implemented in intelligent maintenance systems with minimum human involvement.

An effective prognosis requires performance assessment, development of degradation models, failure analysis, health management and prediction, feature extraction and historical knowledge of faults (1). For an accurate prognosis, it is essential to conduct a prior analysis of the system's degradation process, failure patterns and event history of the machine as well as obtaining quality machine condition data. In addition to accurate prediction of remaining useful life, an ability to provide long-term prediction is one of the challenges in implementing predictive maintenance strategies in real life application. Liu et al. suggested the similarity based method for manufacturing process performance prediction and diagnosis (2). In their paper, similarities with historical data were used to predict the probabilities of failure over time by evaluating the overlap between predicted feature distributions and feature distributions related to unacceptable equipment behaviour for long-term prediction of process performance. However, they only considered two degradation processes, namely, a normal process behaviour and a faulty process behaviour. For accurate assessment of machine health, a significant amount of a priori knowledge of the assessed machine is required because the corresponding failure modes must be known in advance and well-described in order to assess the current machine performance (3). In this paper, to achieve long-term prediction of the remnant life of machine, the authors propose a machine prognostic model based on health state estimation using a modified SVM classifier. In this model, prior historical knowledge is embedded in the closed-loop prognostic system together with the classification of faults and health state estimation. The historical knowledge includes prior knowledge of the machinery degradation process, failure patterns and maintenance history.

This model proposes an integrated approach; accurate prognosis requires good diagnostics information. Li et al. suggested that a reliable diagnostic model is essential for the overall performance of a prognostics system (4). Diagnostics also provides information on obtaining reliable event data and acquiring feedback for system redesign. Therefore, by using an integrated system of diagnosis and prognosis, pre-determined dominant fault obtained in the diagnostic process can be used to improve the accuracy of prognostics in estimating the remnant life. In addition, an integrated system can also deal with different types of faults in a machine system.

The health state estimation is carried out through exploring a full failure degradation process of the machine from new to final failure stages. In terms of the historical knowledge, historical failure data and events will be applied to identify the failure patterns. This approach produces an effective feature extraction and the construction of fault degradation steps for impending faults.

In this research, fault diagnosis and different health states estimation are performed using the classification ability of SVM, with subsequent machine prognostics being conducted based on the probabilities of each health states. The several fault cases of High Pressure Liquefied Natural Gas (LNG) pumps were used to validate the feasibility of the proposed diagnostic and prognostic model. To select effective features for the classification of health states, the effectiveness of features were examined and calculated. The results show that the proposed prognosis model has the potential to be used as an estimation tool for machine remnant life prediction in real life industrial applications.

The remaining part of the paper is organised as follows. Section 2 presents the proposed diagnosis and prognosis model based on utilising a health state estimation with embedded historical knowledge. In Section 3, the basic principle of SVM employed in this research is described briefly. Section 4 presents the results of fault diagnosis and prognosis of High Pressure Liquefied Natural Gas (HP-LNG) pumps. We conclude the paper in Section 5 with a summary for future research work.

2. Integrated Diagnosis and Prognosis Model Based on Health State Estimation

In this research, an innovative prognostics model based on health state estimation integrated with diagnostics is proposed. Figure 1 presents the framework of the diagnostic and prognostics model based on health state estimation using SVM. The proposed system consists of three sub-systems, namely, historical knowledge, diagnostics and prognostics.

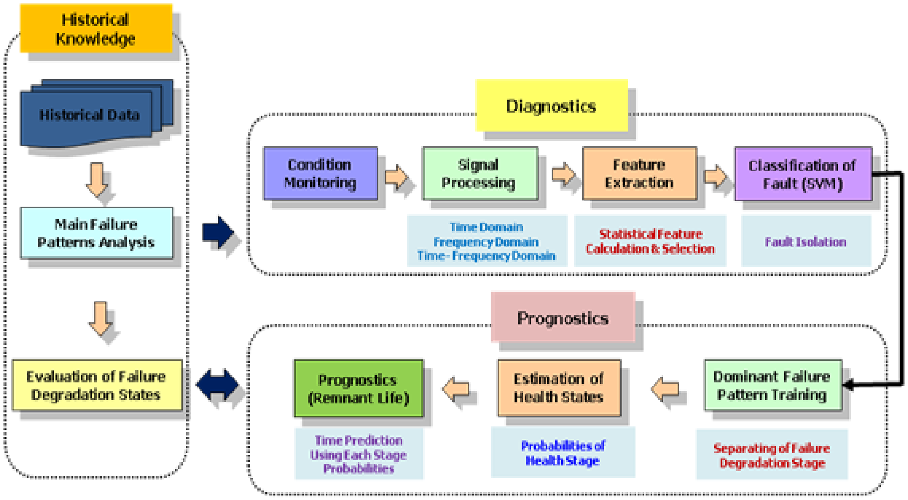

Fig. 1. Framework of the Prognostics System Based on Health State Estimation

In this system, the feature extraction and selection techniques in the diagnosis module are linked with the historical knowledge. Through failure pattern analysis of the historical data and events, failure degradation stages can be determined to estimate the health state of the machine. First, historical condition monitoring data are used in failure pattern analysis in the historical knowledge sub-system. With this prior analysis, major failure patterns that affect the entire life of the machine are identified for diagnostics and prognostics. The failure degradation stages are also determined in historical data analysis.

In the diagnostics sub-system, the condition monitoring data of the machine are collected where significant features of machine faults can be extracted. In general, raw data acquired from sensors require signal processing to obtain appropriate features. A range of features is calculated to cover the preliminary impending faults of the machine system.

The effective selection of features is required to avoid the problem of dimensionality and high training error which may cause computer overload and overfit of training data in the pattern recognition process. An effective feature selection can be used to provide better performance of the predictor, cost-effective predictors and a better understanding of the underlying process that generated the data (5). After feature extraction (feature selection), predetermined major fault data are trained using SVM multi classifier. Through this training of major faults of the machine system, current impending faults can be isolated and identified in the diagnostic system. However, this diagnostic system does not provide the severity of fault.

After identifying the impending fault, the failure degradation stages determined in prior historical knowledge module are employed in health state estimation module as depicted in Figure 1. In this step, predetermined failure stages were trained before testing the current health state. Through prior training of each failure degradation stage, current health condition can be obtained in terms of the probabilities of each health state of the machine. The remaining useful life (RUL) obtained according to the probabilities of each health states and historical operation time can be expressed as Eq (1) accordingly.

$$\boldsymbol{RUL} = \sum_{n=1}^{n} \{(P(S1)T(S1) \cdots P(Sn)T(Sn)\} \tag{1}$$

Where $\boldsymbol{P}$ is a probability of health state, $\boldsymbol{S}$ is health state, $\boldsymbol{N}$ is number of states and $\boldsymbol{T}$ is operation hours.

The final output of the prognosis module on certain impending faults can also be accumulated in the case based data as historical knowledge. This accumulated historical knowledge can then be used for system updating and improving for the prognosis model.

3. Support Vector Machines

Support vector machines (SVMs) have been employed to conduct fault diagnosis and prognosis of machine because of its excellent ability in classification and regression. As an intelligent technique, SVM can train a given data set and save the result as weights, and then use the weights to perform classification. Traditionally, SVM is used for classification of linear data into two classes. However, by using Kernel mapping, SVM can be used to perform the training process and classification of nonlinear data. Furthermore, by optimizing the hyper-plane, SVM can solve classification and regression problems. Nambura et al. [6] presented the possibility of fault severity estimation via SVM for the mode-invariant fault diagnosis of automotive engines.

This section provides a brief summary of the standard SVM for pattern recognition. SVM is based on statistical learning theory introduced by Vapnik and his co-workers [7],[8]. SVM is also known as maximum margin classifier with the abilities of simultaneously minimizing the empirical classification error and maximizing the geometric margin. Given data input $\mathbf{x}_i$ (i = 1, 2… M), where M is the number of samples having corresponding labels $y_i \in \{-1, 1\}$. In the case of linear data, it is possible to determine the hyperplane $f(\mathbf{x}) = 0$ that separates the given input data.

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = \sum_{j=1}^{M} w_j x_j + b = 0 \tag{2}$$

This leads to the following optimization problem with respect to the primal variables $\mathbf{w}$ and b:

$$\text{minimize} \quad \frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{M} \xi_i \tag{3}$$

$$\text{subject to} \quad \begin{cases} y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i, & i = 1,..., M \\ \xi_i \geq 0 & i = 1,..., M \end{cases} \tag{4}$$

Where ξ_i is the noise with slack variables and C is the penalty parameter of error term. This problem can be reduced to the dual quadratic optimization problem as follows which can be solved practically by:

$$\text{maximising} \quad L(\alpha) = \sum_{i=1}^{M} \alpha_i - \frac{1}{2} \sum_{i,j=0}^{M} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \mathbf{x}_j \tag{5}$$

$$\text{subject to} \quad \alpha_i \geq 0, \quad i = 1, \ldots, M. \qquad \sum_{i=1}^{M} \alpha_i y_i = 0 \tag{6}$$

Thus, by solving the dual optimization problem, we derive the non-linear decision function as follows:

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i (\mathbf{x}_i \mathbf{x}_j) + b \right) \tag{7}$$

SVM can also be used in non-linear classification tasks in conjunction with the application of kernel functions. The data to be classified is mapped onto a high-dimensional feature space, where linear classification is possible. Using the non-linear vector function $\Phi(x) = (\Phi_1(x), \ldots, \Phi_l(x))$ to map the n-dimensional input vector $\mathbf{x}$ onto l-dimensional feature space, the linear decision function in dual form is given by

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i (\mathbf{\Phi}^T(\mathbf{x}_i) \mathbf{\Phi}(\mathbf{x}_j)) + b \right) \tag{8}$$

Working in the high-dimensional feature space enables the expression of complex functions, but also generates other problems. Computational problems can occur due to the large vectors and over-fitting can also exists due to the high-dimensionality. The latter problem can be solved by using the kernel function. The Kernel is a function that returns a dot product of the feature space mappings of the original data points and is given by $K(x_i, x_j) = (\Phi^T(x_i)\ \Phi(x_j))$. When applying the kernel function, learning in the feature space does not require explicit evaluation of Φ and the decision function will be

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}_j) + b\right) \tag{9}$$

Any function that satisfies Mercer's theorem [9] can be used as a kernel function to compute a dot product in feature space. There are different kernel functions used in SVM, such as linear, polynomial and Gaussian RBF. The kernel defines the feature space in which the training set examples will be classified. In this research, the polynomial function ($(\gamma\ \mathbf{x}^T \cdot \mathbf{x}_j + r)^d$, $\gamma > 0$) was employed for classification of health states.

SVMs were originally designed for binary classification and there are several methods for multi-class classification, such as "one-against-one", "one-against-all", and directed acyclic graph (DAG). Hsu and Lin [10] presented a comparison of these methods and pointed out that "one-against-one" method is suitable for practical use than other methods. Consequently, in this study, the "one-against-one" method is adopted in diagnosis and prognosis test.

4. Validation Model using High Pressure LNG pump

4.1 High pressure LNG pump

Liquefied natural gas (LNG) takes up six hundreds of the volume of natural gas at or below the boiling temperature (-162℃), which can make storage and transportation much easier. In an LNG receiving terminal, high pressure LNG pumps are used to boost the LNG pressure to 80 bar for evaporation into highly compressed natural gas for it to be delivered via a pipeline network across large distances. The numbers of high-pressure LNG pumps determine the amount of LNG to be received at the terminal. LNG pump is a critical equipment in the production process and need to be maintained at optimal operating conditions. Therefore, vibration and noise of high-pressure LNG pumps are regularly monitored and managed to provide an indication of pump failure based on predictive maintenance techniques.

Table 1 shows the pump specifications. These high-pressure LNG pumps are submerged and operate at super cooled temperatures. They are self-lubricated at both ends of the rotor shaft using LNG. Due to the low viscous value (about 0.16cP) of LNG, the bearings are poorly lubricated which required them to be specially designed.

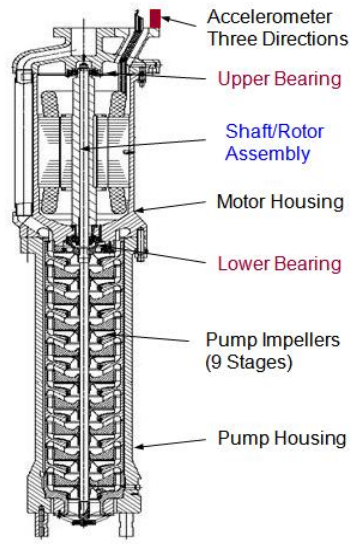

Fig. 2. Pump schematic

It is difficult to detect the cause of pump failure at an early stage because certain bearing components failure can result in rapid total bearing failure as a result of poor lubricating conditions and high operating speed (3,600*rpm*). An abnormal failure will not provide sufficient time to analyze the possible root cause before total pump failure. Due to the material property variations of cryogenic pumps at super low temperatures and the

Table 1. Pump Specifications

Capacity	Pressure	Impeller Stage	Speed	Voltage	Rating	Current
241.8 m^3/hr	88.7 kg/cm^2. g	9	3,585 RPM	6,600V	746 kW	84.5 A

difficulties in measuring the vibration signals on the submerged pump housing, there are some of the problems with the diagnosis of pump health and the study of vibration behaviour. Hence, there is a need to use the historical knowledge of failure patterns for an accurate estimation of remnant life. For long term prediction failures Condition Based Maintenance (CBM) is highly recommended for these pumps. As shown in Figure 2, two ball bearings are installed to support entire dynamic load of the integrated shaft of the pump and motor. The submerged motor and bearings are cooled and lubricated by a predetermined portion of the LNG being pumped. For condition monitoring of the pump, three accelerometers are installed on the top plate close to the upper bearing assembly in three directions.

4.2 Verification of impending fault (Diagnosis of fault)

For the better prediction of machine remnant life, the prior verification of impending fault is essential in this model. Therefore, the fault diagnosis test of LNG pumps was conducted. In this research, authors analyzed the three years historical data of LNG pumps to determine main faults which affect the entire operation life and maintenance schedules. As a result of this analysis, three fault types were decided for machinery fault diagnosis such as bearing fault, excessive rubbing of pump impeller and motor rotor bar fault. Diagnostic tests were conducted using the vibration data of four conditions collected through three accelerometers installed on the pump top plate. These diagnostic tests were also carried out in five different severity levels of three faults to observe the accuracy of classification performance according to the progressive fault levels. Figure 3 shows the spectrum plots of typically three of the faults including the normal condition.

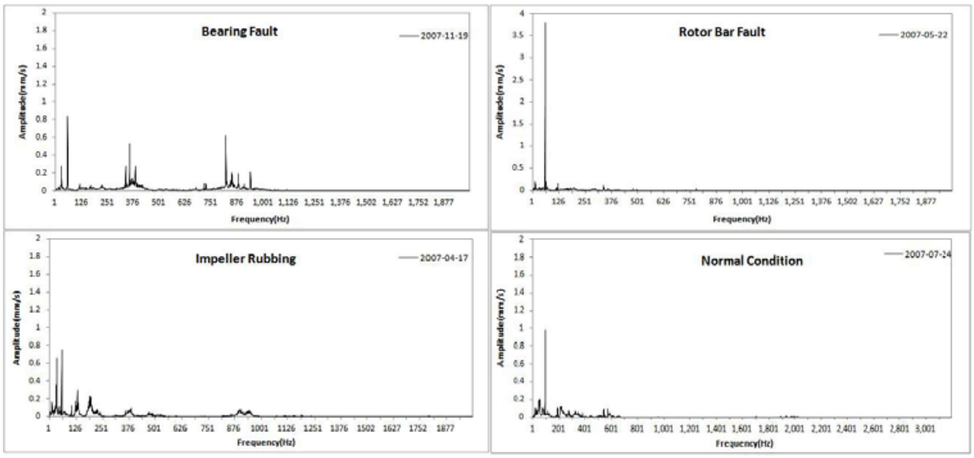

Fig. 3. Spectrum plots of three faults included normal condition

In this paper, 10 statistical parameters from the time domain data were calculated. These feature parameters were mean, rms, shape factor, skewness, kurtosis, crest factor, entropy estimation, entropy estimation error, histogram lower and upper. In addition to these parameters, four parameters (rms frequency, frequency centre, root variance frequency and peak) in the frequency domain were also calculated for diagnostic test. A total of 42 features (14 parameters, 3 positions) were calculated. The acquired vibration data and features from LNG pumps were summarized in Table 2.

In general, effective selection of features is necessary to avoid the problem of dimensionality and high training error value for the classification of fault, known as Feature Selection Problem [11]. In this paper, for the better performance of SVM with the reduction of computational effort, effective features were selected using the evaluation method of

Table 2. Acquired vibration data and features for diagnostic test

Machine No	Fault Type	No of Severity Level	No of Sample	No of Features	Sampling Frequency
P701C	Bearing Fault	5	5	42	8,192 Hz
P701D	Impeller Rubbing	5	5	42	8,192 Hz
P701A	Rotor Bar Fault	5	5	42	8,192 Hz
P701B	Normal	5	5	42	8,192 Hz

feature effectiveness introduced by Knerr et al. [(12),(13)]. High effectiveness value relates to those features which have low dispersibility in the same class and high dispersibility among different classes, which can minimise the classification training error. For a detailed understanding of this evaluation method please refer to the above references. As a result of above evaluation technique, eight features were selected as effective features compared with the other features.

For the five progressive level tests of the four fault conditions, the polynomial function was used as a basic kernel function in SVM classifier. Sequential minimal optimization (SMO) proposed by Platt [(14)] was also used to solve the SVM classification problem. For selection of optimal kernel parameters (C, γ, d), the authors used the cross-validation technique in order to obtain effective classification of performance which is based on Hsu et al. [(15)] so as to avoid the problem of over-fitting or under-fitting in feature space. The one-against-one method was applied to perform the multi-class classification.

The classification results of five progressive levels on four fault condition are summarized in Table 3. In this Table 3, the classification rates of first and second fault level are 75.0% and 90.0% respectively. These poor performances of classification are due to the

Table 3 Fault Classification of Five Fault Levels

Fault Level	Kernel/Multi-SVM	Accuracy (Training/Testing, %)	No of SV's	CPU Time(S)
1	Polynomial/OAO	75/75	16	0.083
2	Polynomial/OAO	90/90	11	0.016
3	Polynomial/OAO	100/100	8	0.017
4	Polynomial/OAO	100/100	7	0.016
5	Polynomial/OAO	100/100	9	0.016

over-fitting of features at the initial four conditions. After the third level of fault, the classification accuracies reach 100.0% and need fewer numbers of SVs than lower fault levels. This result indicates that the fault classification accuracy is variable depending on the severity of machine fault.

4.2 Prognosis of pump failure

After the identification of impending fault, prognostic tests were conducted using two progressive impeller rubbing data to predict the remaining useful life of pump. The acquired vibration data are summarized in Table 4. As shown in Table 4, a total 50 and 55 vibration samples were collected during full pump life for training and testing of the proposed prognosis model, respectively. Although these two impeller- rub cases had different fault severities due to the impeller and shaft bush wear, these faults indicated similar failure patterns over the total operational time.

In this test, 10 statistical parameters from the time domain data and four parameters in the frequency domain were also calculated. A total of 42 features (14 parameters, 3 positions) used in this model.

To select the effective features, the effectiveness factor values calculated from the 42 features according to above mentioned method in diagnosis test. In this research, the authors

Table 4. Acquired impeller rubbing data of the LNG pump

Machine No	Total operation hours	Reason of remove & Root cause	No of sample data	Sampling frequency
P701 B	2,488Hrs	High Vibration & Excessive wear of impellers(#1-7)	50	8,192 Hz
P701 D	2,218Hrs	High Vibration & Excessive wear of impellers(#1-9)	55	8,192 Hz

selected five features (RMS, Entropy estimation value, Peak value, Histogram upper and lower values) because of their high effectiveness factor values as compared with the other features.

In this work, the six health stages were tested to obtain the probabilities of each health stages. Once the six stages were trained using the selected five features from P701 D (55 data sets), similar case data of impeller rubbing (P701 B) which consisted of 50 sample sets were tested to obtain the probabilities of the six degradation stages using SVM classifier. Figure 4 shows the probabilities of each state of P701 D.

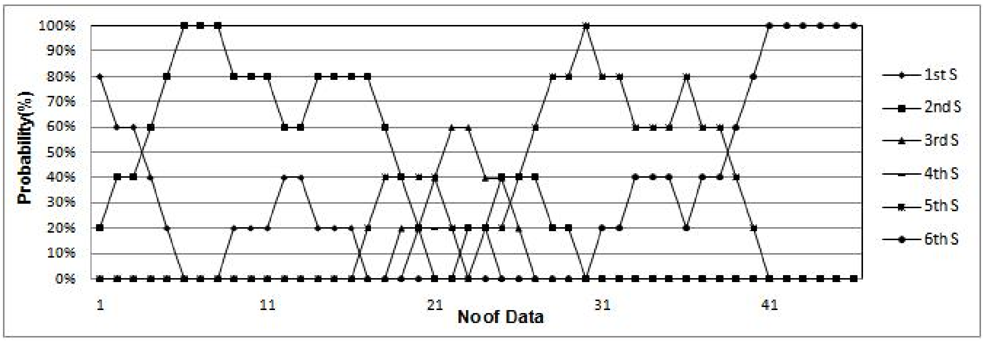

Fig. 4. Probabilities of each state P701 B

The first stage had a probability starting with 80% and decreased as long as the next stage probability increased. The complexity of middle stages in display could be explained due to the uncertainty of machine health condition or inappropriate data acquisitions in real life environment. However, the entire probabilities of each stage explain the sequence of the six degradation stages which are more and less separated.

For the estimation of the remaining useful life (RUL), the expected life of the machine was calculated by using the operation hours for each training data and their probabilities. Figure 5 shows the result of estimated remnant life and a comparison between real remaining life (%) and estimated life (%).

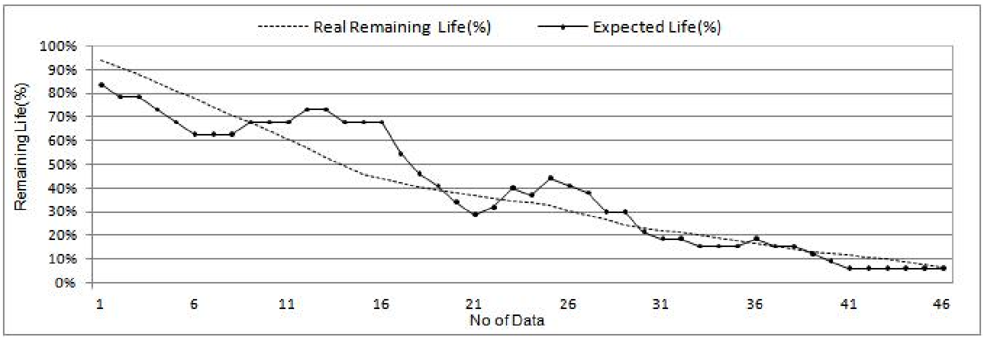

Fig. 5. Comparison of real remaining life and estimated life

As shown in Figure 5, although there are some discrepancies in initial and middle zones, the overall trend of the estimated life follows the actual remaining life of the machine. The average prediction value was 92.7% for the entire range of data set. Furthermore, the estimated life of the final state matched the real remaining life with less than 0.8% of remaining life. The average of prediction error was calculated using the following equation.

$$Average\ prediction\ error = \frac{\sum_{i=1}^{N} \mu_i' - \mu_i}{N} \tag{13}$$

Where N: number of data, μ_i': real remaining life, μ_i: expected life.

However, there are some discrepancies between the calculated remaining life time (Hrs) and real remaining life time (Hrs) as shown in Figure 6. As mentioned above, the estimated time was calculated from training data sets (P701 D) which had 2,218 hours in total operation. Therefore, this difference during the initial degradation states was caused by the discordance of total operation hours between training and test data.

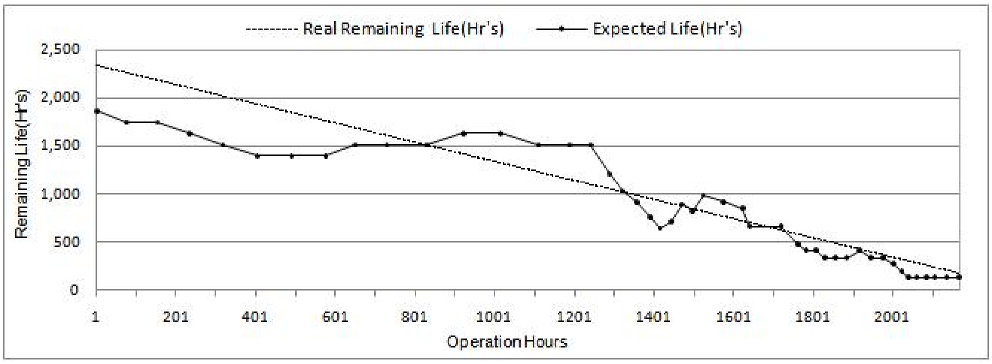

Fig. 6. Comparison of real remaining life time and estimated life time

5. Conclusions

This paper proposed a machine prognostic model based on health state estimation combined with fault diagnosis using SVM. To verify the proposed model, data from three faults including normal condition, from a high pressure LNG pump were used to verify this model. The results of diagnosis test shows that the fault classification accuracy is variable depending on the severity of machine fault.

For the prognosis of pump failure, two sets of data from excessive impeller rubbing were used to predict the remnant life using an SVM classifier. The result from an industrial case study indicates that the proposed prognostic model has the capability of provide accurate health state estimation and a long-term prediction of machine remnant life for industrial applications. However, knowledge of failure patterns and physical degradation from historical data for different types of faults still needs further investigation.

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