Wireless Condition-based Maintenance System for Rotating Machinery

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Abstract: Condition-based maintenance (CBM) presently plays an important role in avoiding unexpected failures, improving machine reliability, and providing accurate maintenance records and activities for rotating machinery. Traditional wired sensors commonly used for gathering data are costly and of limited value in industry. Recently, together with the advancement of sensor technology and communication networks, sensors have been virtually metamorphosed into smaller, cheaper, and more intelligent ones. These sensors are equipped with wireless interface that can communicate with others to form a network. This enables the sensors to be flexibly applicable and the hard cables from the sensors to the data acquisition/analysis system to be eliminated, hence, lead to reduction of the capital and maintenance costs. In this study, a wireless CBM system comprised hardware and software components is proposed to deal with the maintenance issues of rotating machinery. The hardware component consists of wireless sensors and networks used for receiving, processing, and transmitting signals obtained from the machine. The software component is a Matlab graphic user interface which is implemented for data processing and analysis, condition monitoring, diagnostics, and prognostics. The viability of the wireless CBM system for industrial application is presented using the water pump system as a case-study to evaluate the reliability and applicability of this system.

Keywords: Wireless sensors, Wireless sensor networks, Condition monitoring, Diagnostics, Prognostics

1. INTRODUCTION

Condition-based maintenance (CBM) has been known as a cost-effective maintenance strategy for equipment compared to other strategies including corrective maintenance and preventive maintenance. In CBM, equipment operating conditions are continuously monitored to identify incipient faults before they become critical. By providing an early warning of potential failures, preemptive maintenance can be carried out rather than corrective maintenance which is one of the most costly maintenance strategies. CBM is facilitated by health monitoring systems which employ several modules of hardware and software. These modules consist of data collection and analysis, condition monitoring and fault detection, fault diagnostics, prognostics, and activities and maintenance planning. Generally, data collection and analysis module in association with fault detection and condition monitoring module are used for tracking and identifying the system conditions. Once a fault or anomaly is detected, the diagnostic module will determine the type of fault, and in some cases, the severity of the fault. The prognostics module uses all the available information and the results of previous modules to estimate the remaining useful life (RUL) of the system. With this available information, the system operations could be adjusted to mitigate the effects of failure or to slow down the progression of failure, thereby extending the RUL to a point when a scheduled maintenance activity can be carried out.

Traditionally, the health monitoring system is realized in wired systems formed by linking communication cables to the sensors [1]. Although wired systems offer many advantages, they require cables interconnection devices which lead to costly installation, costly maintenance of sensor/cable system to meet stringent environmental effect, and high failure rate of connectors. Alternatively, recent form of health monitoring system is online surveillance system where the monitored data are more frequently measured [2]. In this system, several hardwired sensors are connected to multiplexers, which are networked to a main computer database. However, most of the medium size manufacturing facilities cannot afford to implement such a system due to high up-front capital cost in wiring and sensors, installation challenges, and overall complexity. Therefore, eliminating the cables as well as connectors and reducing the cost of sensors are the main attractions for implementing CBM system in industry.

Recently, the evolution of sensor technology and communication networks, particularly with the introduction of micro-electro-mechanical (MEM) systems, has enabled to design and fabricate the sensors which are cost effective compared to traditional sensors. These sensors not only collect data but also perform some local pre-processing and transmitting their results through wireless communication to the user. This results in the elimination of the wired communication infrastructure. Due to the commercial and computational feasibility mentioned above, wireless sensors and wireless sensor networks (WSNs) have attracted considerable attention and have been applied in various areas such as entertainment, travel, retail, industry, medicine, care of the dependent people, and emergency. Surveys of wireless sensors applications and reviews of various WSN aspects are shown in references [3-6].

Research on the field of wireless sensors and WSNs applied to condition monitoring of industrial systems is relatively new. Korkua et al. [1] proposed and developed a ZigBee based WSN for health monitoring of induction motors in which the vibration signals of rotor imbalance were processed with signal processing techniques to predict the level of severity. Tiwari et al. [7] implemented single-hop sensor network to facilitate real-time monitoring with extensive data processing for a heating and air conditioning plant. A low-cost system used for bearing condition monitoring of induction motors, namely WiBeaM, was proposed by Jagannath and Raman [2]. In this system, the vibration signals were sensed by wireless sensors and transmitted to a central base station by a network of sensor nodes. These data were then analyzed further using signal processing tools for defect diagnostics. Other applications of wireless sensors and WSNs for industrial system condition monitoring and fault detection are shown in references [8-10].

Generally, the above approaches only focused on hardware component application, consisting of wireless sensors and WSNs, to monitor the conditions of industrial system. This is lack of other indispensable parts for determining the fault types and estimating the system RUL. Therefore, the software component contained the core algorithms to perform diagnostic and prognostic tasks is of necessity for a comprehensive CBM system. In recent years, numerous approaches to diagnostic and prognostic algorithms have developed and applied for several areas. In mechanical system fault diagnostics and prognostics, these approaches have been covered in the range from statistical-based to model-based approaches which were summarized and reviewed by Jardine et al. [11] and Heng et al. [12]. However, most of them are used as a standalone unit and only focused on either fault diagnostics or prognostics.

Together with the development of sensor technology and standalone approaches, a comprehensive and applicable CBM system is needed for industrial systems. Hence, a wireless CBM system consisting of the mentioned components is proposed in this paper for rotating machinery. In the proposed system, wireless sensors and wireless sensor unit are housed in the operating machine and used as a hardware component to acquire the vibration and/or current signals. These signals, which are normally in analog form, are then converted to digital form and transmitted to the central base station via the wireless networks. In the central base station, the server receives the signals and continuously transmits to the software component of the system. This component uses Matlab user interface to perform the tasks of data processing and analysis, health condition monitoring, diagnostics, and prognostics. The algorithms employed in the software have been developed from our work and presented in references [13-21]. The proposed wireless CBM system is tested on water pump to demonstrate its effectiveness and reliability in real industrial application.

2. WIRELESS CONDITION-BASED MAINTENANCE ARCHITECTURE

The schematic architecture of the wireless CBM system (WCBMS) is shown in Fig. 1. It consists of several parts to receive and convert the condition signals into useful information for maintainers. Based on this information, the maintainers can carry out remedial actions, inspect the conditions, and conduct necessary repair on the defect before catastrophic failure occurs. As depicted in Fig. 1, the condition signals is obtained from the sensor nodes located at machine and wired to wireless sensor unit (WSU). The WSU is equipped with wireless interface and computational functions for filtering, converting the signal to digital form, and transmitting the measured signals to the central base station. The signals are processed by software modules in the central base station to perform various tasks, such as feature manipulation, diagnostics, and prognostics. A brief introduction of the modules/components in WCBMS is given as follows:

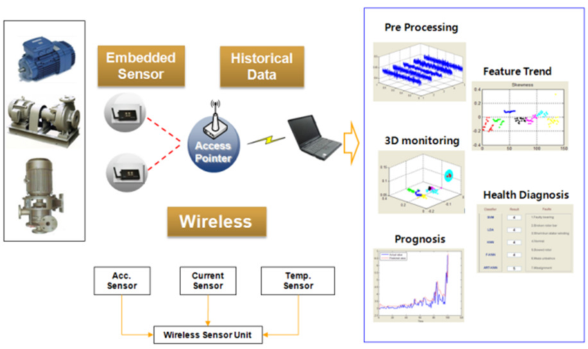

Fig. 1 Schematic architecture of WCBMs

2.1 Wireless sensors and wireless sensor unit (WSU)

In this study, the wireless sensors involve acceleration and current sensors which are based on MEMS technology. The single monolithic IC ADXL321 of Analog Devices, which is a complete dual-axis accelerometer with signal conditioned voltage output, is used for acceleration measurement. It detects acceleration in the range of ±18g and measures both vibration and gravity. The current sensor is a chip CSA-1V, which is a single-axis Hall sensor packaged in a standard integrated circuit housing (SOIC-8) with eight-pin and surface mount design. It senses the current by converting the magnetic field generated by the flow of current through a conductor and produces a voltage which is proportional to that field. The CSA-1V is directly placed on a printed circuit board (PCB) over the current track. The maximum current to be measured depends on the number of loops of the sensor. The PCB and specifications of these sensors are respectively shown in Fig. 2 and Table 1.

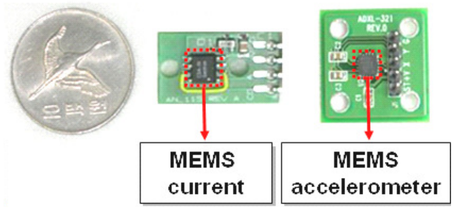

Fig. 2 PCB of MEMS-based current and acceleration sensor

Table 1 Specifications of MEMS sensors

MEMS accelerometer	*MEMS current*
• Name : ADXL-321 • Company : Analog Device • Frequency range : 0 ~ 2,500Hz • Sensitivity : 57mV/g • Shock rage : 10,000g • Power : 2.4 ~ 6VDC • Temperature : -20 ~ 70 (^{o}C)	• Name : CSA – 1V • Company : GMW • Bandwidth : DC ~ 100kHz • Sensitivity : 13 mV/A • Power : 0 ~ 6VDC • Temperature : - 40 ~ 125 (^{o}C)

The wireless sensor unit (WSU) consisting of filter, interface, and wireless LAN modules is wired to the sensors to receive the analog signals. The signals are then filtered by using a high pass filter (HPF) and a low pass filter (LPF). The high pass filter is used to filter out signals with frequency over 0.7Hz, whilst the low pass filter is employed for anti-aliasing. The interface module uses an 8-bit ATmega128 processor to control the 16-bit analog to digital converter (ADC), gain setting and wireless communication. The secure digital memory (SD memory) card in the hardware is used for data backup in case the wireless network is out of order. The last module, wireless LAN module, performs the task of transmitting signals to the central base station. The diagram and specifications of WSU are shown in Fig. 3 and Table 2, respectively.

Table 2 Specification of WSU

Item	Function
Input range	±2.5V
Supply voltage	5V
Operation temp.	-25~60°C
Sensor type	MEMS
A/D resolution	16 bit/channel
Bandwidth	0~4000Hz
Data transfer	WLAN(TCP/IP)

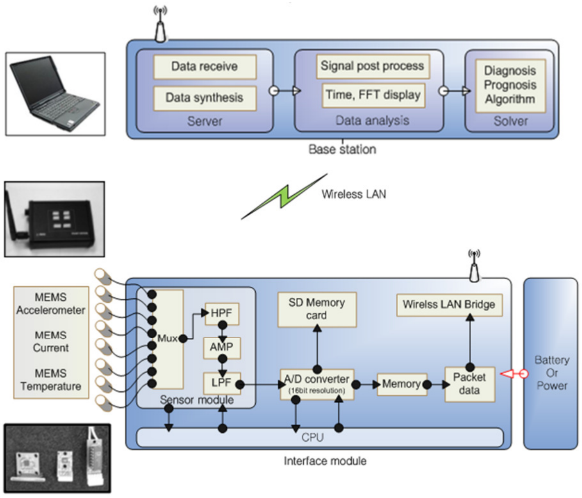

Fig. 3 Diagram of WSU

2.2. Central base station

The central base station is formed by server and software and employed for performing the remaining tasks of CBM. The server is used for receiving and synthesizing the data transmitted from WSU, whilst the software comprises several modules to perform data processing and analysis, condition monitoring, diagnostics, and prognostics. The framework and algorithms implemented for this software are depicted in Fig. 4 and summarized in Table 3. Additionally, a user interface is created as shown in Fig. 5 in order to facilitate the software usage. The function of the software modules are described as following.

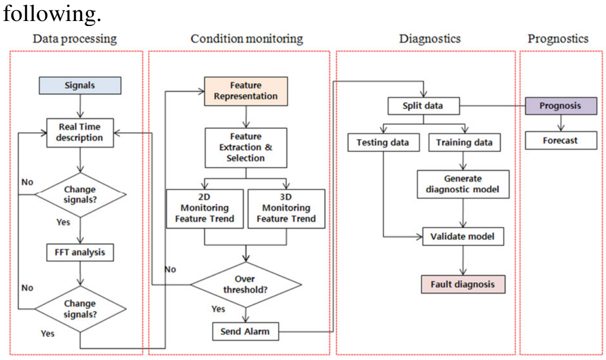

Fig. 4 Framework of software component

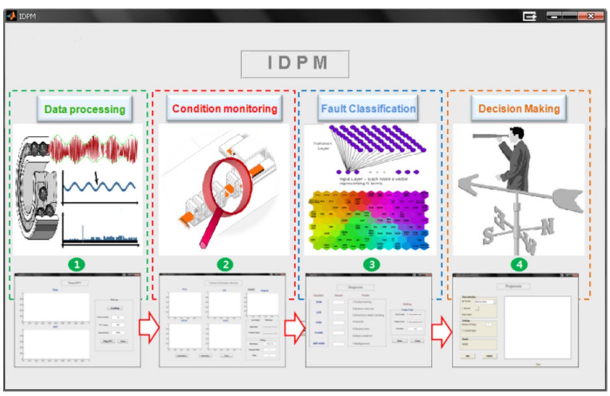

Fig. 5 Software user interface

2.2.1 Data processing and analysis

Data processing is the first module to be used for removing signal distortions, restoring the original shape of signal, removing sensor data which are not relevant, and transforming the signal to produce relevant features more explicitly. Beside traditional functions required to process the measured data, four functions, namely real-time analysis, time-series and waterfall, RMS-order, and FFT analyzer are added to this module for further user assistance:

- *Real-time analysis* is utilized to continuously monitor the signals in the time domain. This enables the users to intuitively detect the fault occurrence by examining the change of signals.
- *Time-series and waterfall* is to assist the user in identifying the time whenever a fault occurs. Furthermore, the band monitoring method is also incorporated in this function to support the user's decision in identifying any significant change in signal frequencies which are widely distributed in certain frequency range.
- *RMS-order* is used to replace the waterfall method if the number of data is huge. In addition, RMS is also employed as a reference to compare the orders of operating speeds which range from 1x to 10x.
- *FFT analyzer* offers useful information on frequency components to the user. Frequency peaks will be displayed corresponding to the calculated fault frequencies inputted by users. In this function, the ball bearing defect frequencies and gear fault frequencies information are collected and embedded.

2.2.2. Condition monitoring

Normally, the data obtained from the previous module is rarely used as machine condition indicators due to high dimension and inadequate characteristics. Therefore, these data are commonly transformed into features to avoid the above mentioned problems. Feature is corner-stone of accurate and reliable fault diagnostics as well as prognostics. To handle the features in this module, three functions which are feature calculation, feature extraction, and feature selection are carried out. Feature calculation is employed for transforming the original data into feature space, while feature extraction is utilized for reducing the dimension of existing features by selecting only significant features. However, the feature set may contain many redundant or irrelevant features as well as salient features after the feature extraction has been done. Consequently, there is a need for the feature selection function to select minimum number of features which can characterize the machine conditions from the whole feature set.

In this study, twenty-one features are calculated with ten features in time domain and three features in frequency domain. The remaining eight features are auto-regression coefficients. The time domain features are mean, RMS, shape factor, skewness, kurtosis, crest factor, entropy error, entropy estimation, and histogram of upper and lower limits. The frequency domain features consist of RMS frequency, frequency center, and root variance frequency. These features are then displayed as two-dimension and three-dimension images to assist the user in identifying the structure of features. To reduce the dimension of these features, feature extraction algorithms are utilized including principal component analysis (PCA), independent component analysis (ICA), kernel principal component analysis (KPCA), and kernel independent component analysis (KICA). In feature selection, the squared Euclidean distance method is chosen as an objective function in this study.

2.2.3. Diagnostic module

This module is used for analyzing the failure pattern embedded in the features to determine the root cause of previous observed faults or degradation. The result of this module provides the health state of machine which is either in normal mode or fault mode, as well as fault type to the users. The five classification methods in this module are support vector machine (SVM), linear discriminant analysis (LDA), k-nearest neighbor (KNN), Fuzzy KNN, and ART-Kohonen neural network (ART-KNN). The purpose of using several classifiers is to increase the reliability and accuracy of the classification results.

2.2.4. Prognostic module

Prognostics is the ability to forecast future machine health or time of fault occurring through evaluating the present state of machine conditions [19, 22]. Popular prognosis methods commonly used are mathematical model based, statistical, and data-driven methods. In this study, the method which combines autoregressive moving average (ARMA) with generalized autoregressive conditional heteroscedasticity (GARCH), namely ARMA-GARCH [20], is used. This module provides useful information to the user to determine the future trend of the machine's health state and decision on the faith of the machine. The algorithms used for condition monitoring, fault diagnostics, and prognostics are summarized in Table 3.

Table 3 Algorithms in software component

Module	*Algorithm*
Data processing	FFT, Waterfall, Band monitoring, Band fault detection, Bearing fault detection, Gear fault detection
Condition monitoring and feature reduction	PCA, ICA, KPCA, KICA
Diagnostics	SVM, LDA, KNN, F-KNN, ART-KNN
Prognostics	ARMA-GARCH

3. APPLICATION OF WCBMS FOR INDUSTRIAL SYSTEM

The applicability and reliability of the proposed WCBMS is verified by implementing it to a water pump system at Korea Water Cooperation. To acquire signals of the pump system, eight wireless accelerometers were installed in vertical and horizontal directions at the ends of motor and pump housing bearing as depicted in Fig. 6. The sampling frequency in this work was 4,096 Hz.

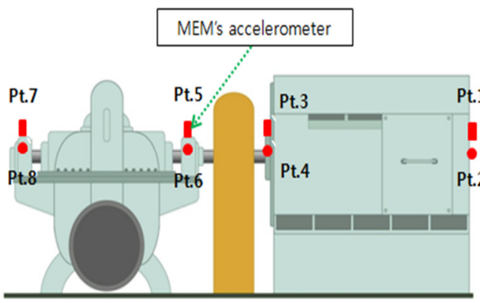

Fig. 6 Experimental apparatus

After processing the measured data by using signal processing techniques, Figs. 7, 8 and 9 respectively show the results of first three functions which are time-series and waterfall, band monitoring, and RMS-order. Fig. 7 plots the time waveform and waterfall of the machine condition with respect to time. Nevertheless, the information provided in this analysis is insufficient. Therefore, the band monitoring shown in Fig. 8 is used to provide more useful and quantitative information. The RMS-order result as depicted in Fig. 9 indicates the historical and current states of the pump system. This figure also indicates that the 1x and 2x orders of the operating speed are larger than other harmonics and have significant effects on this system.

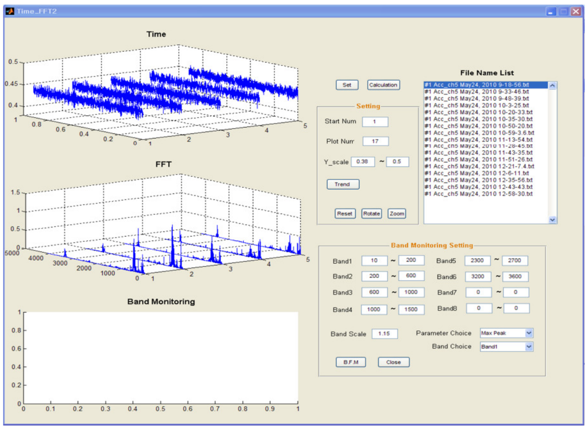

Fig. 7 Results of time series and water fall function

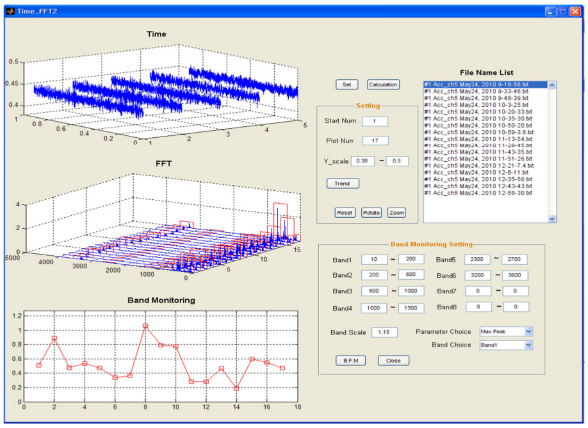

Fig. 8 Results of band monitoring

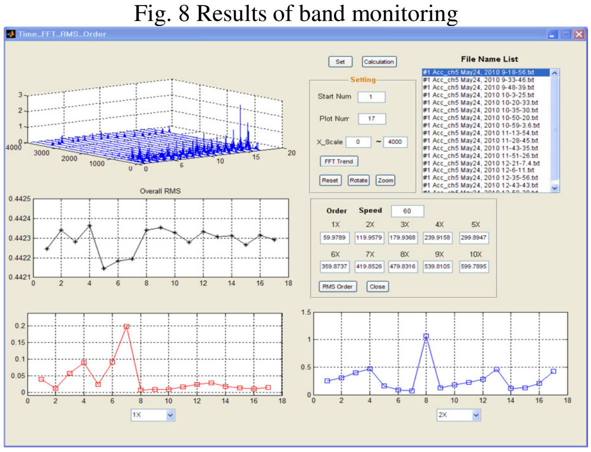

Fig. 9 Results of RMS Order

In the next step, the feature calculation function is applied to generate the twenty one features as mentioned in the previous section. These features are displayed in two-dimensional plot with different colors as shown in Fig. 10.

Based on these features, the feature extraction and feature selection functions are subsequently carried out to reduce the feature dimensions and select the relevant important features. Fig. 11 depicts the results of the four feature extraction methods. These results can assist the user in determining which method is the best one in clustering the feature, and the results could be used for the next iteration. Fig. 12 shows the results of feature selection wherein the features numbered as 1, 3, 5, 6, 9, and 10 are chosen as the best features due to their maximum Euclidian distances from the center of a feature group to each feature.

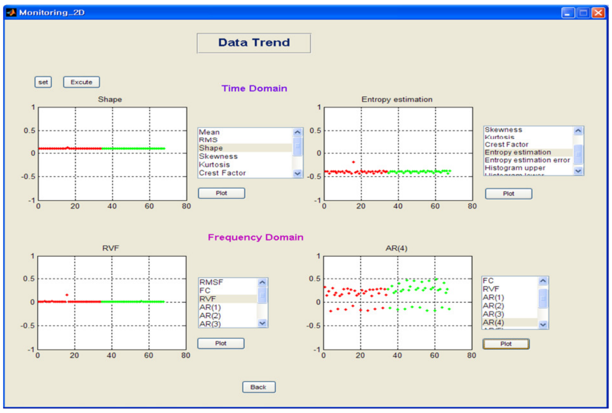

Fig. 10 Results of the feature calculation

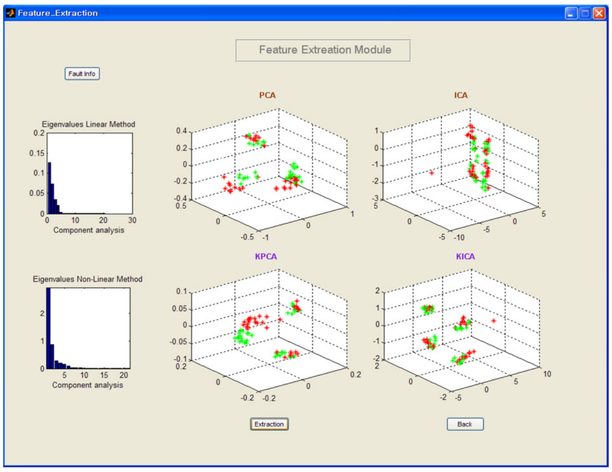

Fig. 11 Results of the feature extraction

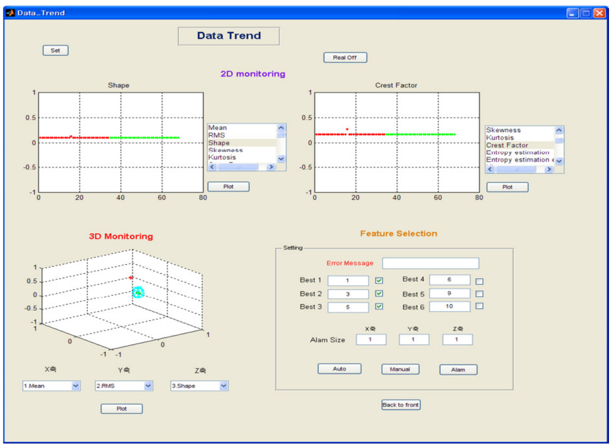

Fig. 12 Results of the feature selection

In the diagnostic module, features obtained from the previous procedure are used for training the diagnostic models which are SVM, LDA, KNN, F-KNN, and ART-KNN. These models are then employed for classifying the pump system health condition. Fig. 13 shows the classification results in which the first four classifiers confirm that the condition of the motor in the pump system as “normal” and the last one shows a “bowed rotor”. This difference could be a misclassification occurred in the ART-KNN method. Therefore, we can conclude that the pump system is in normal operating state. In addition, the forecasted result of the prognostic module shown in Fig. 14 provides information on the future state of system condition in order that necessary actions are required to maintain the operation of the system.

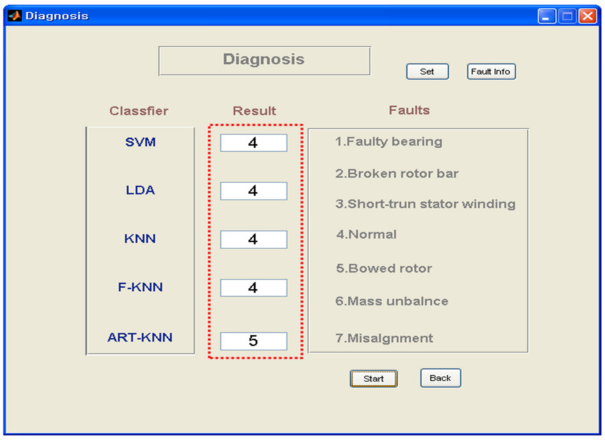

Fig. 13 Results of the diagnostics module

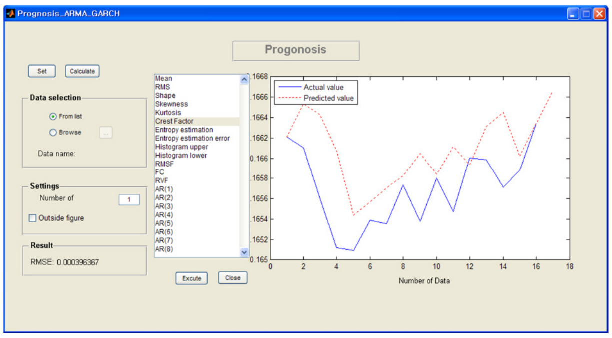

Fig. 14 Results of the prognostics module

4. CONCLUSION

This paper has proposed the complete CBM system, namely wireless CBM system, comprised hardware and software components for rotating machinery. The hardware component consists of wireless sensor and wireless sensor network used for receiving, pre-processing, and transmitting the condition signals of rotating machinery. The software component contains a Matlab graphic user interface consisting of data processing and analysis, condition monitoring, diagnostics, and prognostics modules for processing the signals to determine the current and future health states of the machine. Furthermore, this wireless CBM system is applied for an industrial machine, the water pump system at Korea Water Cooperation, to verify its reliability and applicability. The results indicate that the wireless CBM system can be employed as a complete tool which covers from data acquisition to prognostic capability for maintainers with minimum technical background.

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