Support Vector Machine for Machine Fault Diagnosis and Prognosis*

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Abstract
This paper presents a survey of fault diagnosis using support vector machine (SVM). It attempts to summarize and review the recent research and development of SVM in machine fault diagnosis. Numerous methods have been developed based on intelligent system. However, the use of SVM for machine fault diagnosis is still rare. In addition, this paper introduces the feasibility of SVM based on regression (SVR) for machine prognosis system. The proposed method is addressed to predict the upcoming state of machine based on previous condition. The viability of developed system is evaluated by using trending data of low methane compressor acquired from condition monitoring routine. The results show that SVR has potential and promise for reliable and robust forecasting tool in machine prognosis system.

Key words: Support Vector Machine, Fault Diagnosis, Prognosis, Forecasting

1. Introduction
Since the maintenance has significant impact in industry, it has received a deep attention from the expert and practitioner maintenance. According to study, maintenance costs are a major part of the total operating costs of all manufacturing and production plants, which can make or break a business. Depending on the specific industry, maintenance costs can represent from 15% to 40% of the costs of goods produced (1). In fact, these costs are associated with maintenance labor and materials and are likely to go even higher in the future with the addition of factory automation through the development of new technologies.

Nowadays, the development of maintenance strategy was supported by computer technology both in hardware and software. A recent developed method is using artificial intelligent (AI) techniques as tool for maintenance routine. Based on the idea, how to perform an excellent and easy maintenance program; it leads the practitioners maintenance to create an intelligent maintenance system. Intelligent maintenance should consist of parts (hardware and software) which are possible the system to do maintenance routine in such a way like human being. Application of expert system (ES) as a branch of AI in maintenance is one of solution. The basic idea of ES is simply that expertise, which is the vast body of task-specific knowledge, is transferred from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then, like human consultant, it gives advice and explains, if necessary, the logic behind the advice (2).

Support vector machine (SVM) is a relatively new computational learning method based on the statistical learning theory; can serve as ES. Introduced by Vapnik and his co-workers
SVM becomes famous and popular in machine learning community due to the excellence of generalization ability than the traditional method such as neural network. Therefore, SVM have been successfully applied to a number of applications ranging from face detection, verification, and recognition, object detection and recognition, handwritten character and digit recognition, text detection and categorization, speech and speaker verification, recognition, information and image retrieval, prediction and so on. However, papers which discuss the use of SVM in machine fault diagnosis and prognosis are few.

This paper presents a survey of machine fault diagnosis using SVM. It attempts to summarize and review the recent research and development of SVM in machine fault diagnosis. Until 2006, the use of SVM in machine fault diagnosis is tending to develop towards expertise orientation and problem-oriented domain\(^\text{(6)}\).

In addition, this paper will also introduce the feasibility of SVM based on regression (SVR) for machine prognosis system. A reliable machine prognosis system is very important to predict the degradation condition and fault propagation trend in machines before a fault reaches in critical level. It also can produce an early alarm and warning before catastrophic condition occurred. Machine condition prognosis means the use of available (current or previous) observations to predict upcoming states of machine\(^\text{(7)}\). Compared to fault diagnosis, the papers that concern with prognosis are much fewer.

In recent years, many researchers tend to apply AI techniques due to the ability to be flexible model predictors which can be automatically built by training process without the need for identification of model structures and parameters. The most widely used of AI techniques for forecasting are neural networks and fuzzy system. Zhang and Ganesan\(^\text{(8)}\) used self-organizing neural networks for multivariable trending of the fault to estimate the residual life of a bearing system. Wang and Yachtevanos \(^\text{(9)}\) applied dynamic wavelet neural networks to predict the fault propagation and estimate the residual useful life as the time left before the fault reach a given value.

In present study, SVR is applied to predict time-series of failure trending data of machines. The aims of this study are to investigate the feasibility and to evaluate the performance and reliability of SVR in failure trending data prediction, and also to develop a reliable prognosis system for machines condition prediction.

2. Description of SVM

The linear equation of SVM can be expressed in the form

\[
f(x) = \langle w, x \rangle + b
\]

(1)

where \( \langle , \rangle \) denotes the dot product in \( \mathbb{R}^d \).

In the case of classification task, the samples are assumed have two classes namely positive class and negative class. Each class associates with labels be \( y_i = 1 \) for positive class and \( y_i = -1 \) for negative class, respectively. For linear data, it is possible to determine the hyperplane \( f(x) = 0 \) that separates the given data.

The vector \( w \) and scalar \( b \) are used to define the position of separating hyperplane. The decision function is made using \( \text{sign} f(x) \) to create separating hyperplane that classify input data in either positive class and negative class. A distinctly separating hyperplane can be presented in complete equation

\[
y_i f(x_i) = y_i (\langle w, x_i \rangle + b) \geq 1 \text{ for } i = 1, 2, ..., M
\]

(2)

where \( M \) is the number of samples.

By minimizing \( \|w\| \) subject to this constrain, the SVM approach tries to find a unique separating hyperplane. Here \( \|w\| \) is the Euclidean norm of \( w \), and the distance between the hyperplane and the nearest data points of each class is \( 2/\|w\| \). By introducing Lagrange multipliers \( \alpha_i \), the SVMs training procedure amounts to solving a convex quadratic problem...
The solution is a unique globally optimized result, which has the following properties

\[ w = \sum_{i=1}^{N} \alpha_i y_i x_i \]  

(3)

Only if corresponding \( \alpha_i > 0 \), these \( x_i \) are called support vectors.

When SVM are trained, the decision function can be written as

\[ f(x) = \text{sign} \left( \sum_{i=1}^{N} \alpha_i y_i (x \cdot x_i) + b \right) \]  

(4)

Moreover, in the case of regression, the flatness in the case of Eq. (1) means the one seeks small \( w \). One way to ensure this is to minimize the Euclidean norm, i.e. \( ||w||^2 \).

Formally, the problem of Eq. (1) can be written as convex optimization problem by requiring

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} ||w||^2 \\
\text{subject to} & \quad y_i - \langle w, x_i \rangle - b \leq \varepsilon; \quad \langle w, x_i \rangle + b - y_i \leq \varepsilon
\end{align*}
\]

(5)

The tacit assumption in Eq. (5) is that such a function \( f(x) \) actually exists that approximately all pairs \( (x_i, y_i) \) with \( \varepsilon \) precision, or in other words, that the convex optimization is feasible. However, this may not be the case, or we also may want to allow some errors. Analogously to the soft margin in Vapnik (11), one can introduce slack variables \( \xi_i, \xi_i^* \) to cope with otherwise infeasible constraints to optimization Eq. (5). Hence, we present the formulation stated in reference (5).

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} ||w||^2 + C \sum_{i=1}^{l} (\xi_i^* + \xi_i) \\
\text{subject to} & \quad y_i - \langle w, x_i \rangle - b \leq \varepsilon + \xi_i; \quad \langle w, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^*; \quad \xi_i, \xi_i^* \geq 0
\end{align*}
\]

(6)

The constant \( C > 0 \) determines the trade off between the flatness of \( f(x) \) and the amount up to which deviations larger than \( \varepsilon \) tolerated. The formulation above corresponds to dealing with a so called \( \varepsilon \)-insensitive loss function \( |\xi|_\varepsilon \) described by

\[
|\xi|_\varepsilon = \begin{cases} 0 & \text{if } |\xi| \leq \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{cases}
\]

(7)

The calculation can be simplified by converting into the equivalent Lagrangian dual problem, the decision function of Eq. (6) has the following explicit form

\[
L(w, b, \alpha) = \frac{1}{2} ||w||^2 + C \sum_{i=1}^{l} (\xi_i^* + \xi_i) - \sum_{i=1}^{l} \alpha_i (\varepsilon + \xi_i - y_i + \langle w, x_i \rangle + b) - \sum_{i=1}^{l} \xi_i \eta_i^* (\xi_i^* - y_i + \langle w, x_i \rangle - b) - \sum_{i=1}^{l} (\eta_i \xi_i^* - \eta_i \xi_i) 
\]

(8)

Then, the task is minimizing Eq. (8) with respect to primal variables \( (w, b, \xi_i, \xi_i^*) \) have to famish for optimality.

\[
\frac{\partial L}{\partial w} = w - \sum_{i=1}^{l} (\alpha_i^* - \alpha_i) x_i = 0 
\]

(9)

\[
\frac{\partial L}{\partial b} = \sum_{i=1}^{l} (\alpha_i^* - \alpha_i) = 0
\]

(10)

\[
\frac{\partial L}{\partial \xi_i^*} = C - \alpha_i^* - \eta_i^* = 0
\]

(11)
Substituting Eqs. (9), (10) and (11) into Eq. (8) yields the dual optimization problem.

\[
\begin{aligned}
\text{minimize} & \quad \frac{1}{2} \sum_{i,j=1}^{l} (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) (x_i, x_j) - \varepsilon \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i (\alpha_i - \alpha_i^*) \\
\text{subject to} & \quad \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0; \quad \alpha_i, \alpha_i^* \in [0, C]
\end{aligned}
\]  

(12)

In deriving Eq. (12), the dual variables \( \eta_i, \eta_i^* \) have eliminated through condition Eq. (11), as the variables did not appear in the dual objectives function anymore but only were present in the dual feasibility conditions. Eq. (9) can be rewritten as follows

\[ w = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) x_i \]  

(13)

Therefore, Eq. (1) can be expressed as

\[ f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) (x_i, x) + b \]  

(14)

This is so called support vector expansion, i.e. can be completely described as a linear combination of the training patterns \( x \). The Lagrange multipliers \( \alpha_i \) and \( \alpha_i^* \) represent solutions to the above quadratic problem, which act as forces pushing predictions toward target value \( y \). Only the nonzero values of the Lagrange multipliers in Eq. (12) are useful in forecasting the regression line.

For a linear non-separable case, the dot product of \( \langle x_i, x \rangle \) in Eq. (12), can be replaced with function \( K(x_i, x) \) known as the kernel function. Kernel functions enable the dot product to be performed in high-dimensional feature space using low dimensional space data input without knowing the transformation. All kernel function must satisfy Mercer’s condition (12) that corresponds to the inner product of some feature space. The RBF is commonly used as kernel for regression

\[ K(x_i, x) = \exp\left\{-\gamma | x_i - x |^2 \right\} \]  

(15)

For the variable \( b \) in Eq. (14), it can be computed by applying the Karush-Kuhn-Tucker condition. In this case, the interested readers can refer to reference (13) for detail explanation.

3. Review SVM for fault diagnosis

3.1 Rolling element bearing

Jack and Nandi (14) performed fault detection of roller bearing using SVM and artificial neural network (ANN). They used vibration data taken from small test rig and simulate the bearing condition which has four faults: inner race fault, outer race fault, rolling element fault and cage fault. They defined and calculated statistical features based on moments and cumulants and selected the optimal features using GA. In the classification process, they employed SVM using RBF kernel with constant kernel parameter. Yan and Shao (15) employed SVM for fault detection of roller bearing using vibration signal and noise. Unfortunately, there is no special method in their research except SVM classification routine. However, they stated that SVM has promising application in fault diagnosis. Moreover, Samanta et al. (16,17) have improved the previous methods in fault detection of bearing. They applied GA for feature selection and searching proper RBF kernel parameters. Several effect conditions such as sensor location, signal preprocessing, number of features were presented to show the performance of SVM compared with ANN. Rojas and Nandi (18,19) have improved their previous research on bearing fault diagnosis. They proposed a practical scheme for fast detection and classification of rolling element bearing. Sequential
minimal optimization was implemented for solving SVM optimization problem. Zhang et al. (20) proposed probabilistic SVM for fault diagnosis of bearing. It was aimed to effectively reduce the number of samples on the condition of keeping the classification accuracy. Sugumaran et al. (21) employed fault diagnosis of roller bearing using decision tree (DT) and proximal SVM (PSVM). DT was aimed to identify the best features from a given set of samples for the purpose of classification. They claimed that PSVM has the capability to efficiently classify the faults using statistical features. Recently, Hu et al. (22) proposed a method that used improved wavelet package transform and SVM ensemble for fault diagnosis of rolling element bearing. They also employed feature selection using distance evaluation technique due to its reliability and simpleness.

3.2 Induction motors

Induction motor is a critical component in many industrial processes. It is also frequently integrated with any commercially available equipment and the process itself. Therefore, it has been urgently required special attention in condition monitoring to guarantee the performance of induction motor. Early fault diagnosis during its operation will give the incipient faults condition, and then the efforts to overcome any faults should be done to avoid more serious condition.

Pöyhönen et al. (23,24) proposed method namely coupling pairwise SVM for fault classification of induction motor. Power estimate density using Welch’s method was calculated from circulating currents in parallel branches of motor. Zhitong et al. (25) carried out fault detection of induction motor using SVM technique for detecting broken rotor bars. In their experiment, induction motor was experimented with no fault, one broken bar, two broken bars and three broken bars. Fang (26) conducted a faults diagnosis system based on integration of rough set theory (RST) and SVM. He used stator current spectrum as inputs. RST can perform feature extraction and reduction for removing redundant attributes. Widodo and Yang (27-29) employed fault diagnosis method using SVM combined by feature extraction via component analysis (PCA, ICA, KPCA and KICA). The statistical feature in time domain and frequency domain from current and vibration signal were calculated as features representation. Recently, they conducted fault diagnosis of induction motor based on start-up transient current signal. Transient current signal has characteristic (similarity) that was difficult to distinguish among faults. Therefore, they proposed wavelet SVM (W-SVM) for obtain a novel method in classification process. The basic idea of W-SVM was constructing a kernel function using wavelet function and then inducing into SVM theory (30, 31).

3.3 Machine tools

Ramesh et al. (32) presented a hybrid SVM-Bayesian Network (BN) for predicting the thermal error in machine tool according to specific condition. In this research, SVM-BN was developed first all to classify the error into groups depending on the operating condition and then carry out a mapping of the temperature profile with the measured error. The other research was carried out by Sun et al. (33, 34) who classified tool wear using SVM based on manufacturing consideration. This research was aimed to propose a new performance evaluation function for tool condition monitoring (TCM). Cho (35) was conducted TCM for tool breakage detection using SVM in milling process. SVM was addressed to recognize process abnormalities and initiate corrective action during a manufacturing process. They applied support vector regression (SVR) for tool breakage determination and claimed better than traditional multiple variable regression approach.

3.4 Pump, compressors, valve and turbine

Detection of pump failure has been carried out by Tax et al. (36) using support vector data
description. The importance of preprocessing data was also highlighted in this paper such as feature extraction and selection. Gao et al. (37) applied SVM for fault diagnosis of valve in reciprocating pumps. As preprocessing, the wavelet packet transform was employed to extract feature vectors from vibration signal. SVM was successful applied for fault diagnosis of turbo-pump rotor by Yuan et al. (38). The original data came from vibration signal then the feature extraction was performed by applying PCA to extract the optimal features and reduce the dimension of features. In addition, based on same data Yuan (39) was also carried out fault diagnosis of turbo-pump using SVM with parameter optimization. In this research, artificial immunization algorithm was used to optimize parameters in SVM.

Yang et al. (40) performed condition classification of small reciprocating compressor for refrigerator using SVM. In this paper, wavelet transform and statistical method were used to extract salient features from row noise and vibration signal. In addition, they also carried out cavitation detection of butterfly valve using SVM (41). The other research using SVM for fault diagnosis of reciprocating compressor was performed by Ren et al. (42). This research was aimed to detect valve fault using vibration signal. In turbine detection, Li et al. (43) employed SVM for fault diagnosis of steam turbine. Ensemble learning based on genetic algorithm, namely direct genetic ensemble was performed to achieve good performance in classification. Zhang et al. (44) successfully applied fuzzy support vector machine (FSVM) for condition monitoring of flue-gas turbine set based on vibration signal. FSVM modified separating hyperplane by adding fuzzy coefficients to every training data sample in order to indicate loss difference of misclassifying training data sample of different types.

3.5 HVAC machines

Batur et al. (45) presented fault detection of heat exchanger using SVM combined by least squares parameter identification technique to permit on-line monitoring. The other research was conducted by Han et al. (46) for hot spot detection in power plant boiler air preheater based on least squares support vector machine (LS-SVM). In this system, a discriminate model of 3 pairs of fire status has been built based on LS-SVM using RBF kernel and polynomial kernel. Receiver operating characteristic curve showed that LS-SVM has good classification and generalization ability. Choi et al. (47) carried out fault diagnosis of chillers machine using SVM based on statistical test such as generalized likelihood ratio.

3.6 Other machines

Rychetsky et al. (48) employed support vector machine for engine knock detection. In this research, support vector was combined by kernel adatron technique to provide non linearity, a bias and soft margin. This kernel adatron algorithm was reported can be convergence fast and proper for combination with SVM. Xu et al. (49) employed rough set theory combined with SVM for fault detection of diesel engine. Fault diagnosis of diesel engines is difficult problem due to the complex structure of the engine and the presence of multi-excite sources. Hu et al. (50) developed method called fusion multi-class SVM for fault diagnosis of diesel engine. The main idea of this method is combining the information of several sources then constructs it as an input space. In addition, an application of fault diagnosis in sheet metal stamping operation was conducted by Ge et al. (51). They used strain signal of stamping process which are highly nonlinear and non-stationary and it was typical signal in metal forming process. Samanta (52) carried out gear fault detection using SVM combined with GA. The time domain vibration signal of a rotating machine with normal and defective gears are processed for feature extraction. The extracted features from original signal were used as inputs to SVM classifier.
4. Case study

A case study is presented to give description in using SVM for machine condition prognosis. This case study is based on experimental work in a real system.

4.1 Performance measures

The verification performance statistic, such as the root-mean square error \( (RMSE) \) and correlation statistic coefficient \( (R) \) are used to examine the system. \( RMSE \) provides a general illustration of the overall accuracy of the prediction as they show the global goodness of fit, given as

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{16}
\]

where \( N \) represents the total number of data points in the test set; \( y \) represents the observed value and \( \hat{y} \) represents the predicted value. \( R \) measure the linear correlation between the actual and predicted value, it can be calculated as

\[
R_{y,\hat{y}} = \frac{Cov(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}}, \quad Cov(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}}) \tag{17}
\]

where \( R \) is correlation coefficient and \( Cov (y, \hat{y}) \) is covariance between observed and predicted values. \( \bar{y} \) is the mean of the observed value and \( \bar{\hat{y}} \) is the mean of predicted value. The standard deviation of the observed and predicted values, \( \sigma_y \) and \( \sigma_{\hat{y}} \), respectively, can be calculated as

\[
\sigma_y = \left( \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2 \right)^{1/2}, \quad \sigma_{\hat{y}} = \left( \frac{1}{N-1} \sum_{i=1}^{N} (\hat{y}_i - \bar{\hat{y}})^2 \right)^{1/2} \tag{18}
\]

4.2 Experiment

The proposed method is validated by applying in real system to predict the trending data of a low methane compressor (Figure 1). This compressor is driven by a motor 440 kW, 6600 volt, 2 poles with operating speed 3565 rpm. The related information of system is summarized in Table 1.

<table>
<thead>
<tr>
<th>Male Rotor Vertical</th>
<th>Male Rotor Horizontal</th>
<th>Male Rotor Axial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suction Vertical, Horizontal, Axial</td>
<td>MTR DE/NDE Horizontal</td>
<td>MTR DE/NDE Vertical</td>
</tr>
<tr>
<td>Abnormal position</td>
<td>CMS Off-line Monitoring</td>
<td>CMS On-line Monitoring</td>
</tr>
</tbody>
</table>

(100 mV/ G Accelerometer) (only Horizontal)

The data used in this experiment are trending data of peak acceleration and envelope acceleration. Trending data were recorded from August 2005 to November 2005 which consists of 400 points. This data contains information of machine history (vibration amplitude) with respect to time sequence which can be regarded as time-series. The proposed method is addressed to predict future condition of vibration amplitude based on the previous state. SVR predictor will learn the characteristic of previous state and save it as weights, bias and support vectors to perform prediction.

Fig. 1 Low methane compressor: wet screw type.
Table 1 Description of system

<table>
<thead>
<tr>
<th>Motor</th>
<th>Compressor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage</td>
<td>6600 V</td>
</tr>
<tr>
<td>Power &amp; Pole</td>
<td>440 kW, 2 Pole</td>
</tr>
<tr>
<td>Bearing</td>
<td>NDE/#6216, DE/#6216</td>
</tr>
<tr>
<td>RPM</td>
<td>3565 rpm</td>
</tr>
<tr>
<td>Lobe</td>
<td>Male rotor (4)</td>
</tr>
<tr>
<td>Female rotor</td>
<td>(6)</td>
</tr>
<tr>
<td>Thrust bearing</td>
<td>7321 BDB</td>
</tr>
<tr>
<td>Radial bearing</td>
<td>Sleeve</td>
</tr>
</tbody>
</table>

4.3 Results and discussion

Figure 2 shows the trending data of peak acceleration of compressor. This data consists of 400 points measurement that represents the machine conditions. At the beginning, condition of machine is normal as shown in the figure that the peak acceleration is almost constant until point 300. Over point 300, amplitude drastically increased that means the condition is changed and degradation condition is occurred. Moreover, it indicates that some faults are occurred in the machine that changes the amplitude significantly.

![Fig. 2 Peak acceleration of compressor.](image)

![Fig. 3 Model validation using peak acceleration.](image)

The proposed method is aimed to predict the future state of machine based on previous conditions. Data from normal state are used to train the proposed system for building the model, and then model will be employed to forecast the future condition of machine. The first 300 data are used for training the system and validating the model, while the remains are used for testing the performance of system.

Training process is performed using 5-fold cross-validation to select the kernel parameters of RBF kernel function. Cross-validation process gives proper kernel parameters $\gamma = 0.25$ and $C = 1$, and $\epsilon$-insensitive loss function is defined equal to 0.001. The result of model validation is presented in Figure 3 that gives RMSE and $R$ are 0.035 and 0.70, respectively. The validated model cannot catch the minimum amplitude due to poor of training. However, the error presented by RMSE reaches 0.035 is acceptable to be a model although the correlation is small (0.7) because the minimum of amplitude cannot be caught by the model.

Figure 4 depicts the performance of testing using future independent data (100 data points) that is never used in training process. The result seems over prediction that cannot approach actual trending data of peak acceleration. RMSE reaches 4.67 is relatively high enough so it may not be a good prediction model. Even though the correlation presented by $R$ is 0.7 shows the poor correlation between the predicted value and the actual one, however, the trending of predicted value is relatively similar to the actual data.

The reason why this model has poor performance is the training data do not contain extreme (or relatively close to extreme) value of amplitude. As intelligent system, if the system is experienced by relatively close to the extreme value so it might be able to catch the actual values. The other reason is the trending data of peak acceleration is drastically changed when it represents the degradation condition of machine. So the model suffers
difficulty to catch the actual values.

Figure 5 demonstrates the trending data of envelope acceleration of low methane compressor. The proposed method is addressed to predict the future state condition of machine based on learning from previous condition. First 300 data are used to train the system for building and validating the model. The remains of 100 data are targeted as actual value that will be predicted by model. The model should predict the maximum value of amplitude that represents the machine degradation or fault occurrence. SVM is trained by training data using 5-fold cross validation for RBF kernel parameters selection. Cross-validation process gives proper kernel parameters $\gamma = 4.5$ and $C = 1$, and $\epsilon$-insensitive loss function is defined equal to 0.001. The result of model validation is presented in Figure 6(a) that gives $RMSE$ and $R$ are 0.075 and 0.98, respectively. The validated model can catch very well the dynamic system represented by training data. Therefore, the model is acceptable and can be considered to be a model as a predictor for system forecasting. The performance of prediction is depicted in Figure 6(b) that shows the acceptability of the model. $RMSE$ reaches 0.085 is relatively small that means the values of predicted data and actual data are very close. Also, the correlation measure $R$ is high, 0.99 which represents the predicted values and the actual one are high-correlated. In this case, the training process is well performed due to good quality of training data that are close-related among others. It means there are no extreme differences (drastically change) between amplitudes of envelope acceleration. So the prediction using SVR model can perform well.
5. Conclusion

This paper presents a survey based on a literature review of the use SVM in machine fault diagnosis. Until 2006, it can be said that only few papers found in this application rather than other areas such as described in section introduction. In this paper, the feasibility of SVM for prognosis system has been studied. The model predictor is built based on the ability of SVM for regression technique. The proposed method is validated to predict the future state condition of a low methane compressor based on given previous state data. Two cases have been studied using peak acceleration and envelope acceleration. The results show that the proposed method has potential to be a prediction tool for prognosis system based on time-series prediction.

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