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Support vector machine based estimation of remaining useful life: current research status and future trends †

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Abstract

Estimation of remaining useful life (RUL) is helpful to manage life cycles of machines and to reduce maintenance cost. Support vector machine (SVM) is a promising algorithm for estimation of RUL because it can easily process small training sets and multi-dimensional data. Many SVM based methods have been proposed to predict RUL of some key components. We did a literature review related to SVM based RUL estimation within a decade. The references reviewed are classified into two categories: improved SVM algorithms and their applications to RUL estimation. The latter category can be further divided into two types: one, to predict the condition state in the future and then build a relationship between state and RUL; two, to establish a direct relationship between current state and RUL. However, SVM is seldom used to track the degradation process and build an accurate relationship between the current health condition state and RUL. Based on the above review and summary, this paper points out that the ability to continually improve SVM, and obtain a novel idea for RUL prediction using SVM will be future works.

Keywords: Degradation model; Prognostics; Remaining useful life; Support vector machine

1. Introduction

Prognostics and health management (PHM) has attracted much attention because it can conduct timely maintenance, provide spare parts and prevent accidents [1, 2]. The core of prognostics is to estimate remaining useful life (RUL) of some key components [3]. In the field of prognostics, RUL is an important concept that means the residual useful life on an asset at a particular time [4, 5]. A prognostic model predicts RUL of a component by assessing its degradation level from its expected normal health condition. Usually, the predicted RUL is distributed, as a result of inference based on the established model and the uncertainties among feature extraction, degradation modeling, condition estimation and RUL prediction. Prognostics can be generally classified into five types: classifying models, knowledge based models, life expectancy models, artificial neural networks, and physical models [6]. Early signals of wear, aging, and fault conditions may be correlated with a degradation model. Physics-based failure mechanisms are the conventional algorithms related to damage propagation. In practice, it may be difficult to build a physical model for a specific system. Alternatively, one can employ data-driven approaches if run-to-failure data are available [7].

Data-driven based prognostics usually uses pattern recognition and machine learning techniques to train historic data. Data-driven based prediction methods for a nonlinear system include regression-based models [4], Wiener process [4, 8], Gamma process [9], stochastic filtering-based models [4], covariate based hazard models [4], hidden Markov models [10], and hidden semi-Markov models [11-13]. During the last decade, much attention on data-driven based prediction methods has been paid to the use of support vector machine (SVM). SVM, which considers a structure risk, has a better generalization ability compared with conventional machine learning methods, such as artificial neural networks. Better generalization ability means that this method can be applied to other fields more easily.

SVM was first proposed by Cortes and Vapnik [14] for data analysis and pattern recognition and is mainly used for classification and regression.

Fig. 1 shows the basic principle of SVM for classification. The lines $|\mathbf{w}\bullet x_i + b| = 1$ are the boundaries for classifying two different categories A and B. In Fig. 1, two categories A and B are represented by circles and squares, respectively: d is the distance between the two boundary lines. In classifying problems, a larger d means a better classification accuracy, so we should minimize $|w|$.

Many have improved the performance of the normal SVM to solve the problem that SVM can only handle a small num-

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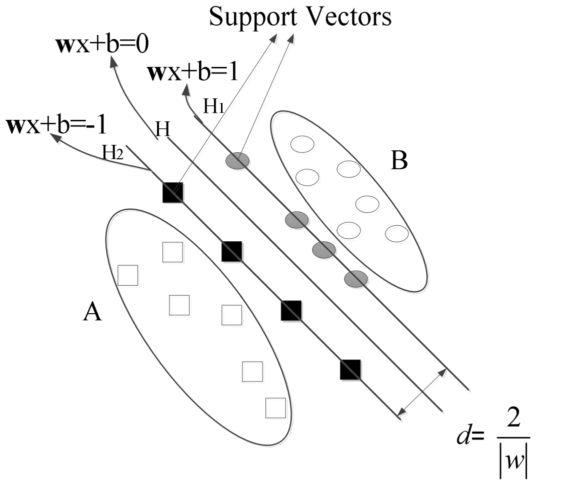

Fig. 1. SVM for classification.

ber of samples and avoid the “curse of dimensionality” [15]. SVM is based on statistical learning theory and can be used to map a nonlinear relationship in a low-dimensional space to a linear relationship in a high-dimensional space. In 2002, Boswell [15] made a deep introduction of SVM and prospected the future use of SVM. In 1997, Drucker et al. [16] proposed support vector regression (SVR) to handle regression problems. SVR has an advantage in a high dimensional space because optimization of SVR does not depend on the dimension of the input space.

The optimization of SVR aims to minimize $|w|$. Considering the influence of prediction errors, a relaxation factor could be added to the optimization formula given as follows:

$$\min\frac{1}{2}\|w\|^2 + C(\sum_{i=1}^{l}\xi_i + \xi_i^*) , \quad (1)$$

where ξ_i and ξ_i^* are relaxation factors and C is a penalty factor. For a nonlinear problem, kernel functions are useful to map data into a high-dimensional space. Some commonly used kernel functions are as follows [17]:

(1) Linear function: $K(x,y) = x\bullet y$

(2) Polynomial function: $K(x,y) = [x\bullet y+1]^d$

(3) Radial based function: $K(x,y) = e^{-\|x-y\|^2/2\sigma^2}$

(4) Two layer neural network function:

$K(x,y) = \tanh(kx\bullet y - \delta)$,

where x is the coordinate value in the original space and y is the new coordinate value in a high-dimensional space.

Li et al. [18] and Lin and Wang [19] introduced a fuzzy membership function to SVM for solving the effect of noise, which is useful for solving some practical engineering problems. Suykens and Vandewalle [20] proposed least square support vector machine (LSSVM) to enhance the computing complexity of SVM [21]. Brabanter [22] then proposed a robust LSSVM based on the distribution of error variables. Brabanter et al. [23] presented a bias-corrected confidence band for an LSSVM based on regression framework. Suykens and Vandewalle [20], and Brabanter [22] made major contributions to refine LSSVM. Suykens and Vandewalle [20] discussed the least square version of SVM classifiers. Brabanter [22] introduced the applications of least square SVR to deal with large-scale data. Based on the SVR and the LSSVM, Qu and Zuo [24] introduced an LSSVR-based method for online system condition prognostics, in which the condition indicators were predicted based on noisy observations. Also, Lingras and Butz [25] described the relationship between support vector machine and rough patterns, and set upper and lower boundaries for regression problems. This method can strike a balance between the lower regression constraints and the prediction accuracy. Khemchandani and Chandra [26] introduced twin support vector machine to solve pattern cognition problems. Zhao et al. [27] then used a twin support vector machine to resolve prediction objects. These two methods are both in the framework of the twin support vector machine. The twin support vector machine can solve two related SVM-type problems, each of which is smaller than the original SVM.

Si et al. [4] emphasized that it is better to use data-driven methods for prediction of RUL. SVM is one kind of data-driven method. Hence, this paper provides a review of over 90 references within the last 10 years on RUL prediction using SVM and aims to discuss different applications of SVM to the prediction of RUL. The references reviewed in this paper are classified into two categories: improved SVMs and their applications to RUL prediction. When applying the improved SVMs to RUL prediction, the published methods can be further divided into two types: one, to predict future status of the object to be monitored and then build a relationship between its future status and RUL; the other, to directly build a relationship between its current status and RUL.

The rest of this paper is organized as follows. Sec. 2 introduces a basic procedure to estimate RUL using SVM. Sec. 3 introduces improved SVM algorithms and then reviews their applications for estimation of RULs. Sec. 4 discusses the usability of RUL estimation methods based on SVM. Conclusions follow in Sec. 5.

2. Basic procedure of RUL prediction

The basic procedure of RUL prediction using data-driven method is shown in Fig. 2, in which degradation modeling and RUL prediction are two significant parts in the whole system.

Siegel et al. [28] showed a framework for predicting bearing failure and compared different prediction methods. A general procedure from the initial monitoring information to the final RUL prediction can be divided into three steps. Various kinds of sensors can be used to collect data from the monitored component, such as temperature, acceleration, velocity, and so on. Based on these data, historical health condition can be tracked by some features. Wang et al. [29] used vibration signals of a gear in a gearbox to construct a health index to reflect its deterioration. Once the health index exceeds an adaptive threshold,

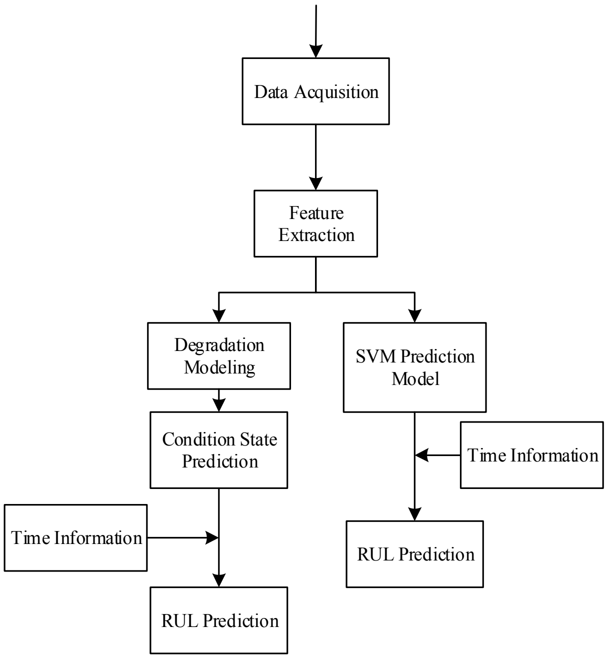

Fig. 2. The procedure of RUL prediction.

the early gear fault can be identified. Consequently, with the help of feature extraction, features can be used to reflect the health conditions and describe the deterioration trend of the monitored component. Based on these features, SVM can be used to construct a degradation model because SVM is excellent in processing multi-dimensional data, for example, data collected from different sensors. Also, using an SVM-based estimation method, multistate estimation can be obtained by classifying the degradation conditions into multistates.

Usually, a degradation model is related to failure time through connecting historic data with failure events. Bayesian based models are useful to link monitoring information with RUL. Here, unknown parameters can be obtained via the maximum likelihood estimation method. In addition, features used for building a degradation model can be regarded as inputs of SVM, and remaining times are regarded as outputs of SVM. Once new monitoring data are input to the trained SVM, the parameters of the SVM are automatically updated and an extrapolation of the SVM to reaching a failure threshold can be used to estimate the RUL of a system or a component.

3. RUL Prediction based on SVM

Using SVM to predict RUL can be classified into two types: one is improved algorithms to predict RUL, i.e., combining it with other algorithms to improve the accuracy of SVM; the other is applications of SVM to predict RUL of components. The scheme of this section is illustrated in Fig. 3.

3.1 SVM based RUL prediction algorithms

Many scholars have focused on the improvement of SVM

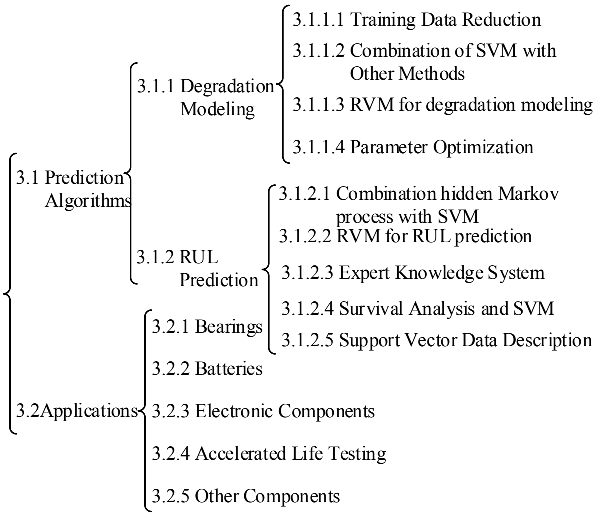

Fig. 3. Summary of RUL predictions using SVM.

performance for some specific applications. Using SVM for predicting RUL has to depend on some software to handle big data. In this paper, we refer to the MATLAB SVM toolbox and LIBSVM, which can implement the functionality of SVM and SVR. LIBSVM was developed by Lin and Chang [30] for the purpose of applying SVM on engineering applications more effectively. This is one of the most commonly used tools in the research on SVM to predict RUL. RUL prediction is closely related to machine performance degradation, and the analysis of degradation process is a basis to predict residual life [31]. The basic step to predict RUL is to obtain monitoring status and to preprocess these data to generate a degradation trend. Using this trend, the RUL estimation model can be obtained [32, 33].

3.1.1 Degradation process modeling

RUL is closely related to the degradation process. Benlalli and Hadjadj [34] emphasized the importance of vibration analysis because most degradation processes can be reflected by vibration features. To predict the RUL, the first step is to analyze the degradation process.

Filtering methods are widely used to process monitoring data. Kalman filtering is a conventional method to process monitoring information. Sikorska et al. [6] mentioned that the Kalman filter is a computationally efficient recursive digital processing technique for estimating the state of a dynamic system. Carr and Wang [35] proposed an extended Kalman-filtering method and combined it with condition monitoring information to recursively establish a conditional probability density function for RUL of a component. Carr and Wang [35] introduced a basic procedure to establish a model for prediction of RUL, and this procedure is also applicable to SVM as well. Cao and Tian [36] discussed disadvantages of the Kalman filtering for monitoring data processing and suggested to use SVM to predict the future life of the monitored object. This method can predict the degradation trend of a fault process more accurately. Dong and Luo [37] predicted the bearing degradation process based on PCA (principal component analysis) and optimized LS-SVM (least square SVM). LS-LSVM was used to train the selected features that can reflect the degradation process. The remainder of this section describes several methods, e.g., training data reduction, combination of SVM with other methods, relevance vector machine (RVM) and parameter optimization of the SVM modeling, to build degradation models based on SVM.

3.1.1.1 Training data reduction

Sufficient training data can improve training precision, while data redundancy will increase the calculation complexity. Sensors can provide many kinds of monitoring data about equipment status and a number of features. Dimensionality reduction facilitates classification, visualization, communication, and storage of high-dimensional data, which provides a method to deal with multivariable problems [38]. It is important to choose a tradeoff between training accuracy and calculation complexity. The way to process training data is important in the applications of SVMs. Farquad et al. [39] proposed a feature extraction method based on SVM. The proposed hybrid rule extraction procedure can use a reduced training set to train the machine learning techniques and this method outperforms the stand-alone intelligent technique. Huang [40] designed a reduced SVM to analyze regression problems. In Ref. [40], the normal SVM has difficulty in processing large scale data sets and cannot deal with the unbalance among different numbers of samples. The method proposed in Ref. [40] was proven more efficiently than the normal SVM for large scale data.

Standard SVM is computationally infeasible for large scale data, so Tsang et al. [41] scaled up kernel methods to approximate the optimal solution and proposed core vector machine (CVM) algorithm. Experiments results show that the CVM is as accurate as the existing SVM, but is much faster and can handle much larger data sets than existing scale-up methods.

Wang et al. [42] illustrated that the SVM decision function is fully determined by a subset of training data, which are called support vectors. It is important to remove irrelevant vectors from training sets. Two new methods were proposed to select subsets of training data. Bi et al. [43] described a method for performing variable ranking and selection using SVM. This method dramatically reduces the number of variables.

3.1.1.2 Combination of SVM with other methods

Zhong et al. [44] presented a three-stage method to process monitoring data. First, wavelet packet transform and time-domain statistical features were used to extract features from monitoring data. Second, the compensation distance evaluation technique was applied to select optimal features via sensitivity ranking. Finally, the optimal features were inputs of the SVMs to predict faults and realize prognostics. Kang et al. [45] used wavelet packet analysis and SVM to process monitoring data. The standard deviations of wavelet packet coefficients of vibration signals, which have been normalized and the dimensions reduction using PCA, were considered as feature vectors to train SVM. Besides, the parameters of SVM were optimized by particle swarm optimization. Pan et al. [46] used improved wavelet packet decomposition and support vector data description (SVDD) to assess bearing performance degradation, and SVDD were used to train the designed health index. Wang et al. [47] used SVDD to fuse multiple health indicators to diagnose early gear faults and assess gear performance degradation. Benkedjouh et al. [48] presented a method based on PCA and SVDD for bearing fault prognosis, in which PCA was used to reduce the dimensionality of vibration features and SVDD was used to fit training data to a hyper-sphere.

Hao et al. [49] used SVM classifiers to recognize different bearing faults. The “one to others” SVM algorithm is adopted to distinguish different bearing faults under eight working conditions. Even though the number of samples is small, the testing accurate is high. Kim et al. [50] used the expanded multi-class SVM for the diagnostics of the turbo-shaft engine, with the artificial neural network (ANN) based on the real coded genetic algorithm (RCGA) to obtain the magnitude of defects and improve the convergence and the accuracy. Wei et al. [51] presented an SVM predicting model based on chaos theory. It adopted SVMs as nonlinear predictors. The number of input variables of the network was determined by computing reconstruct phase space’s saturated embedding dimension. The maximum effective forecasting steps were then determined by computing chaos time series’ largest Lyapunov exponent. Yuan and Li [52] presented a new method using binary tree to construct hyper-planes, to partition a class in each steps and eliminate blind areas, and applying sphere-structured support vector machines (SSVM) for fault diagnosis. Yang and Zhang [53] studied the influence of cost functions, kernel functions and parameters on prediction performance of SVMs. They also compared the performances of different kernel functions, including sigmoid, radial basis function (RBF), polynomial, and linear in the predicting process and found that the RBF kernel performed better than other kernel functions in a long term prediction. Kadri et al. [54] proposed a hybrid algorithm of a binary ant colony and SVM to improve the classification accuracy by an appropriate feature subset with low computational complexity.

3.1.1.3 Relevance vector machine (RVM) for degradation modelling

Based on the normal SVM, using Bayesian inference to describe SVM, called relevance vector machine (RVM), is a new method to solve regression and classification problems. Zio and Di Maio [55] used RVM, which is a Bayesian elaboration of SVM, for degradation model identification, degradation state regression and RUL estimation. They also combined RVM and model fitting in a prognostic procedure for estimating the RUL of a machine component based on data collected on a degradation trajectory. Wang et al. [56] took advantage of RVM and a conditional three-parameter capacity degradation model to realize prognosis of lithium-ion batteries. The RVM is used to derive the relevance vectors that can be used to find the representative training vectors containing the cycles of the relevance vectors and the predictive values at the cycles of the relevance vectors. This method transforms the monitoring vibration signals into features that can be used to track the health condition of the bearing and then to estimate its RUL.

Caesarendra et al. [57] proposed a combination of relevance vector machine (RVM) and logistic regression in order to assess the failure degradation and predict the remaining useful life. RVM was selected as an intelligent system then trained by using run-to-failure bearing data and target vectors of failure probability. Nicolaou et al. [58] proposed a novel output-associative relevance vector machine (OA-RVM) regression framework that augmented the traditional RVM regression by being able to learn non-linear input and output dependencies. The experimental results show that the OA-RVM regression outperforms the traditional RVM in terms of prediction accuracy.

3.1.1.4 Parameter optimization

Cross-validation is the most common method used in SVM models to improve the training accuracy and to help users find optimal parameters. Duan et al. [59] introduced k-fold validation in detail. Cross-validation is popular for estimating generalization error and there are several versions. In k-fold cross-validation, the training data are randomly split into k mutually exclusive subsets (the folds) of approximately equal size. The SVM decision rule is obtained using $k-1$ of the subsets and then tested on the subset left out. This procedure is repeated k times, and each subset is used for testing once. Averaging the test error over k trials gives an estimate of the expected generalization error.

Besides the development of new algorithms to process monitoring data introduced in the previous paragraphs, optimization of parameters in SVM is another hot topic. Penalty factor (C) and parameters used in kernel functions, like σ in RBF, are common parameters. SVM classification optimization problems are similar to SVM regression problems, and parameter optimization mechanism is analogous in a sense. Liu et al. [60] presented a formula to compute the optimal σ (a parameter in RBF) under the principle of maximizing the class separability in a kernel space. The method for determining the parameter σ is an exhaust search algorithm and the grid search, but the computation loads of these two methods are high. Scholkopf et al. [61] introduced a parameter v to effectively control the number of support vectors. This method has proven useful in eliminating the accuracy parameter ε used in the regression case and the regularization constant C in the classification case. They gave the actual meaning of v that is related to the breakdown point of the corresponding robust estimator.

Grid search method is a common optimization way to find the best parameters. Besides this method, intelligent methods are more and more useful in parameter selection. Lorena and de Carvalho [62] introduced genetic algorithms (GA) and developed GA to search for an optimized set of parameters in multiclass problems. Yuan and Wang [63] regarded the SVM parameter selection for function approximation as a compound optimization problem and used a mutative scale chaos optimization algorithm to search for optimal parameter values. Chaos optimization algorithm is an effective way for global optimization. Huang and Dun [64] proposed a PSO-SVM (particle swarm optimization SVM) model that hybridized the PSO and SVM to improve the classification accuracy. This optimization mechanism can realize the input feature selection and the SVM kernel parameter setting.

3.1.2 RUL prediction

The prediction of RUL is closely related to the monitoring data. Zhao and Feng [65] introduced a nonlinear state space model to predict the RUL. State information is an observation sequence. The relationship between monitoring data and RUL can be linked together [66]. The nonlinear state space model can provide a direct relationship between the degradation model and the predicted RUL based on Gamma process. Shen et al. [67] proposed an SVR-based generic multi-class solver to identify the different fault patterns of rotating machinery. Liu et al. [68] designed a modified probabilistic SVM regression (PSVR) method, which is based on the Bayesian probabilistic paradigm with a Gaussian prior distribution. The procedure of this method can be briefly described as: preprocessing for data reconstruction, model selection, and PSVR for estimation of prediction interval and conditional predictive distribution of the target of interest.

Engineering assets are operating in dynamic conditions and are sensitive to environmental changes, and real-time monitoring and prediction can help engineers get timely information about equipment [69]. To solve the timeliness issue of prediction, Benkedjouh et al. [70] recommended an online process and an offline process to predict the RUL of bearings. The purpose of offline process is to learn the degradation models, and the isometric feature mapping reduction technique and SVR are used to predict the RUL. This method is based on a given threshold related to failure. After analyzing the offline data, the user can determine this threshold. If the predicted signal is below the threshold, it means the asset is in a normal state. If it is close to the threshold, the asset is on the verge of breakdown. Hu et al. [71] proposed a real-time lifetime prediction method on the basis of wavelet SVM and fuzzy C-mean clustering. For the products having nonlinear performance degradation paths and limited performance degradation data for each individual, this method can take full advantage of performance degradation of the same kind of products in individual real-time lifetime prediction. This method is similar to the work done by Wang et al. [12] who presented a similarity-based approach for estimating RUL in prognostics, and created a degradation pattern library with the help of data from multiple units of the same system. The data from a test unit are to patterns in the library. The actual life of these matched units is used as the basis to estimate RUL. The biggest advantage of this method is that it can solve the problem when lacking failure data.

Main methods to predict RUL using SVM are listed in the following categories: Markov process with SVM, RVM, expert knowledge system, and survival analysis with SVM.

3.1.2.1 Combination hidden Markov process with SVM

A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. An HMM can be considered as the simplest dynamic Bayesian network. Combination hidden Markov with SVM can utilize the advantages of both. Altun et al. [72] and Kang et al. [11] combined SVM and discrete hidden Markov process to realize fault diagnosis and prognostics. This hybrid method extracts features from monitoring signals effectively and forecasts the RUL more accurately. Valstar and Pantic [73] used a hybrid SVM/HMM to model time in the classifier. The results showed that modeling the temporal dynamics by the hybrid SVM-HMM classifier attained a statistically significant increase of precision than SVM. An HMM is a common method nowadays for RUL prediction.

Besides hidden Markov process, the combination of the Bayesian approach and SVM is another popular method to improve the performance of SVM.

3.1.2.2 Relevance vector machine for RUL prediction

An RVM is a machine learning technique for solving regression and classification problems. RVM has nearly an identical function form to SVM; however, the ways that they are formulated and used are dramatically different [74]. Tipping [75] introduced the general Bayesian framework for obtaining sparse solutions to regression and classification tasks.

Di Maio et al. [76] combined RVM and exponential regression to estimate the RUL. The RUL estimation for the degrading component was performed by resorting to a combination of RVM followed by model fitting onto the identified relevance vectors. This is an attempt to improve conventional methods that are either purely data-driven, or incorporating the physics of the process into the computation, or solely model-based, which cannot accommodate for un-modeled effects and can diverge quickly in the presence of unanticipated operating conditions.

Hu and Tse [77] developed an approach combining RVM with the sum of two exponential functions to predict the degree of wear and the RUL of field pump impellers. Through RVM learning process, a sparse dataset can be obtained for prediction. Compared with stand-alone exponential fitting, the proposed RVM-based model was much better in predicting the remaining useful life of pump impellers.

3.1.2.3 Expert knowledge system

Kim et al. [78] described a technique for accurate assessment of the RUL of machines based on prior expert knowledge embedded in closed loop prognostics systems. Effective intelligent models using condition monitoring techniques and failure pattern analysis for a critical dynamic system can lead to a robust prognostics system. For accurate assessment of machine health, a significant amount of *a priori* knowledge about the assessed machine or process is required. The technique proposed in Ref. [78] used SVM for classification and evaluation of health for bearing degradation. There are six failure degradation stages in the bearing system. SVM is used to classify these different stages. They built a prediction system which consists of three sub-systems: expert knowledge, diagnostics and prognostics. The prognostics sub-system can be used to estimate the RUL.

3.1.2.4 Survival analysis and SVM

Apart from the above items, Widodo and Yang [79] discussed intelligent machine prognostics systems using survival analysis (SA) and SVM. SA utilizes censored and uncensored data collected from condition monitoring routines and then estimates the survival probability of machine components. SVM is employed to predict failure time of individual unit of machine components.

A health index was used by van Belle et al. [80] to build a prediction model. They showed the modified SVM can be used for survival analysis. The proposed method is able to predict the ordering of complex survival times. The resulting machine and its nonlinear kernel version are derived and are related to SVM. Survival time sampled from an accelerated failure time distribution was used for validation. Artificial data were created to compare the proposed method with standard models for survival analysis.

3.1.2.5 Support vector data description

Support vector data description is a pattern classification method based on structural risk minimization that can be used to detect anomalies. Benkedjouh et al. [48] presented a method for fault prognosis of bearing using SVDD. In Ref. [48], SVDD is used to fit trained data which are called health indicators and these indicators can reflect degradation process of bearings.

Pan et al. [46] considered SVDD an excellent method of one-class classification, with the advantage of robustness and high computation. They extracted feature vectors from normal signals and calculated the distance departing from the normal health condition for reflecting degradation process of bearings. Through the above introduction, it is seen that only normal data are used to train SVDD.

Zhu et al. [81] discussed that SVDD model can lead to over-fitting problems and other disadvantages, so they proposed a rough SVDD. The degradation assessment results of bearings showed that RSVDD can improve the performance of SVDD. Shen et al. [82] proposed using fuzzy SVDD and running time to build a monotonic degradation assessment index of rolling bearings.

Chen et al. [83] proposed a novel algorithm based on SVDD and relative distance to predict the fault trend of machinery. Frequency-domain features and kernel functions were optimized in training SVDD. The relative distances in a kernel space between diagnostic samples and the distributed sphere were introduced to decide which fault state the samples belong to.

3.2 Applications of SVM to predict RUL

When using SVM, the data collected from the monitored object are usually divided into two parts: training datasets and testing datasets. Training datasets are used to build models and find the optimal model parameters with the information extracted from training datasets. The traning set only shows the ability of 'learning'; however, a good learner may lack the adequate generalization ability to predict reliable results. Testing datasets are used to measure the prediction performance by accurancy or other penalty functions based on objectives of prognostics. For example, the evaluation of prediction perfor-mace could be measured by score functions, Hamming distance, penalty for an over- or under-estimate, a performance class and so on. The method is evaluated according to practical problems. More details are discussed in the following applications of SVM-based RUL estimation. The objects to be assessed include bearings, batteries, electronic components, and other machine components.

3.2.1 Bearings

Bearings are important mechanical elements used to support the rotation of shafts, and the accurate prediction of their RULs is significant for preventing machine breakdown and reducing economic loss. Di Maio et al. [76] combined RVM and exponential regression for bearing RUL estimation. They acquired a series of degradation data on partially degraded rolling contact thrust bearings and tested their models on real-world vibration-based degradation data. The most relevant basis functions identified on the smoothed and preprocessed data by RVM were fitted to the degradation model, which was then extrapolated to failure for estimating the RUL of the machine component.

Unlike the method of Di Maio et al. [76], Sun et al. [84] extracted features from bearing vibration signals as the inputs of SVM models. The output was the ratio of the bearing running time and bearing failure time. SVM models of different bearings are allocated different weights, and the combination of these models is used to predict RUL of a new bearing.

Kim et al. [85] developed a health state probability estimation method to predict RULs of bearings. This method uses SVMs to estimate the health state probabilities and makes long-term predictions reliable. Shen et al. [86] estimated the RUL of the rolling bearing under limited condition monitoring data based on relative features and multivariable SVM (MSVM). The relative root mean square was used to assess the performance degradation and sensitive features were selected as input by correlation analysis, while MSVM was structured to predict RUL, which has the advantage of multivariable prediction and small sample prediction.

3.2.2 Batteries

Lithium-ion batteries are widely used in electrical vehicles for safety and lifetime-optimized operation. The battery is thus a common research target in RUL prediction. Nuhic et al. [87] used SVM for estimation of the state of health (SOH) and RUL of batteries. As the estimation of SOH and RUL is strongly influenced by environmental, ambient, and load conditions, this method processes data with respect to these factors, including even the operation history. Internal state variables of batteries are either inaccessible or hard to measure under operational conditions. Saha et al. [88, 89] used RVM to improve the traditional prediction methods, such as autoregressive integrated moving average (ARIMA) and extended Kalman filtering (EKF). Their model is incorporated into a particle filter framework, where statistical estimates of noise and anticipated operational conditions are used to provide estimation of RUL in the form of a probability density function. The developed model not only provides a mean estimation of the time to failure, but also generates a probability distribution over time.

Park and Jeong [90] proposed two alternative approaches for predicting the lifetime of a secondary rechargeable batteries. In the recursive SVR, they converted the relating issue into a nonlinear regression problem with right-censored failure time data.

3.2.3 Electronic components

Electronic components appear more and more in complex systems, and the research on their diagnostics and prognostics is of importance in PHM. Electronic components are sensitive to subtle condition changes and their RUL prediction can help users to take timely measures to improve the performance of the whole system. Guo et al. [91] presented an optimal SVM to diagnose the electronic system fault and forecast RUL. They improved a chaos particle swarm optimization algorithm to achieve parameter optimization for the optimal SVM.

Long et al. [92] used LS-SVM to identify failure modes or components in the potential subsystems. This can help to find the potential failure of subsystems or components for complex electronic systems such as radar, aviation systems, and then repair or replace them before the whole system fails. This method is useful for condition-based maintenance (CBM) of complex electronic systems.

3.2.4 Accelerated life testing

Accelerated life testing can help to find the weakness of products and improve the design in manufacturing. Yin and Wang [93] proposed a practical model to predict the life of the items in accelerated life testing based on SVM. This model can reflect the relationship among the stress levels, the reliability and the life of the items. SVM is used to establish a non-parameter model of the accelerated life testing, and the life under a normal stress level can be predicted using life data under high stress levels. Li et al. [94] used SVM to predict time-to-failure in accelerated degradation testing (ADT). Constant stress ADT is studied and ADT data are divided into several sets of performance degradation in different stress levels. Using the SVM prediction model, all degradation processes are predicted to failure and lifetimes are obtained, then life and reliability under normal condition are evaluated by accelerated models. The main target is electronic or photoelectric products, so temperature is the primary typical environmental factor. During the testing process, a single temperature stress is the only factor. Park and Jeong [90] proposed two nonparametric methods, the scale-accelerated degradation path model and the recursive SVM, for analyzing the accelerated life testing data. They combined degradation paths and failure times to estimate the lifetime of the products. Lifetime can be estimated for the censored samples by recursively using the nonparametric Kaplan-Meier estimator.

3.2.5 Other machine components

Other applied areas for RUL prediction are relatively dispersed. Xu et al. [95] used SVM to establish a life prediction model to forecast the life of casings in gas wells. Risk indexes are defined as input vectors and the casing life is the output vector of this model. Liu et al. [96] predicted RUL of water injection pipelines using SVM, and corrosion factors which influenced the life of pipelines most are the input vectors. Using LIBSVM, they established an RUL prediction model. Xu et al. [97] used LS-SVM to predict the life of the barrels of tank guns. They compared different predicted lives through different parameters. Xu [98] proposed a new grey SVM model combining the superiority of SVM forecasting and grey accumulated generating operation. According to the extracted gyro lifetime index (the vibration energy trend), the grey SVM model is exploited to forecast and analyze the RUL of the dynamically tuned gyroscope. Yan et al. [99] applied SVM to assess rotor life loss severity in the power industries. SVM has no limits of the dimensions of input vectors, and the computational time is quite short. Kim et al. [100] use the SVM classifier to estimate the health state probability, to predict the remaining useful life of pump with two sets of impeller-rub data.

Table 1. Summary of degradation models using SVM.

Method	References
Reduced SVM	Farquad et al. [39] Huang [40] Tsang et al. [41] Wang et al. [42] Bi et al.[43]
Combination SVM with wavelet analysis	Zhong et al.[44] Kang et al. [45] Pan et al. [46]
Combination SVM with other theories	Wang et al.[47] Hao et al. [49] Kim et al. [50] Wei et al. [51] Yuan and Li [52] Yang and Zhang [53] Kadri et al. [54]
Relevance vector machine	Zio and Di Maio [55] Wang et al. [56] Caesarendra et al. [57] Nicolaou et al. [58] Benkedjouh et al. [48]

Table 2. Summary of RUL calculation methods using SVM.

Method	References
SVR and threshold	Benkedjouh et al. [70]
Hidden Markov and SVM	Altun et al. [72] Valstar and Pantic [73] Kang et al. [11]
RVM and exponential regression	Di Maio et al. [76] Hu and Tse [77]
Similarity-based approach	Hu et al. [71] Wang et al. [12]
Prior expert knowledge and SVM	Kim et al. [78]
Survival analysis and SVM	Widodo and Yang [79] Van Belle et al. [80]
SVDD	Pan et al. [46] Benkediouh et al. [48] Zhu et al. [81] Shen et al. [82] Chen et al. [83]

4. Discussion

In Sec. 3, we reviewed the use of SVM for RUL prediction. The use of SVM on RUL prediction is discussed in this section. Table 1 summarizes the main SVM-based methods to build degradation models (Sec. 3.1.1).

A summary of RUL prediction using SVM (Sec. 3.1.2) is shown in Table 2, which summarizes RUL calculation methods using SVM. Table 3 lists the main applied fields of RUL prediction methods based on SVM.

Applications of SVM are limited to the research fields shown in Table 3. Prediction of RUL focuses on several objects, for example, bearings and batteries, while the applications to other objects are seldom reported. Through analyzing Tables 1-3, some tips can be summarized as follows:

(1) Methods used for both building the degradation models and predicting the RUL are usually a combination of SVM with other methods. For the use of SVM, parameter selections of SVM usually turn out to be a common optimization problem that can be solved by some advanced algorithms, such as genetic algorithm, particle swarm optimization, and so on.

(2) SVM is a powerful tool for building degradation models, but it is still a tool to predict RUL on the basis of degradation models. Monitoring state information and lifetime are linked by other methods, e.g., conditional probability. A link degradation model with lifetime is still limited and more attention should be paid to this topic.

(3) Applications of SVM to predict RUL are still limited.

Table 3. Applications of RUL prediction based on SVM.

Object	Methods	References
Bearings	RVM	Di Maio et al. [76]
	SVM	Sun et al. [84]
	State probability and historical knowledge	Kim et al. [85]
	Relative features and multivariable SVM	Shen et al. [86]
Batteries	SVM	Nuhic [87]
	RVM	Saha et al. [88] Saha et al. [89]
	Recursive SVM	Park and Jeong [90]
Electronic components	Optimal SVM	Guo et al. [91] Long et al. [92]
Accelerated life testing	SVM	Yin and Wang [93] Li et al. [94]
	Recursive SVM	Park and Jeong [90]
Other machine components	Grey SVM	Xu [98]
	SVM or LSSVM	Xu et al. [95] Liu et al. [96] Xu et al. [97] Yan et al. [99] Kim et al. [100]

According to the reviewed conferences in this paper, the RUL predictions of bearings and batteries are two main application fields. SVM could be applied to estimate RULs of other key components, such as gearboxes, turbine blades and so on.

5. Conclusions

SVM is widely investigated and used to solve engineering problems because of its ability to deal with nonlinear problems. Moreover, the decision function provided by SVM is only determined by a small number of support vectors, which makes SVM promising in utilizing some useful data from many redundant data for RUL estimation. Many experts developed this estimation algorithm by combining SVM with other methods, such as wavelet analysis, Bayesian, hidden Markov, and so on. According to the discussion mentioned in Sec. 3.2, the applications of SVM to RUL prediction are still limited to the prognosis of bearings and batteries. More studies related to other key components need to be investigated in the future.

Till now, most of the RUL estimation methods based on SVM are a kind of data-driven methods that depend on sufficient monitoring information, which is a bottleneck for some cases, where limited monitoring data are available. In addition, if the machine to be monitored operates in a harsh working condition, background noise will corrupt data generated by the monitored objected and increase the difficulty to extract useful features from the monitoring data. Besides, it is critical to select appropriate sensors to avoid the effects caused by environmental changes. Therefore, increasing the quality of monitoring information and then extracting useful features are significant for future research work on RUL estimation.

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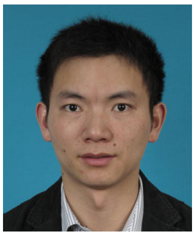

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