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Failure and reliability prediction of engine systems using iterated nonlinear filters based state-space least square support vector machine method

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ABSTRACT

Failure and reliability prediction in engine systems have attracted much attention over the past decades. However, this task remains challenging due to the stochastic nature and dynamic uncertainty of failure and reliability time series data. Two novel approaches for reliability prediction are developed in this study by integrating least square support vector machine (LSSVM) and the iterated nonlinear filters for updating the reliability data accurately. In the presented methods, a nonlinear state-space model is first formed based on the LSSVM and then the iterated nonlinear filters are employed to perform dynamic state estimation iteratively on reliability data with stochastic uncertainty. The suggested approaches are demonstrated with two illustrative examples from the previous literature and compared with the existing neural networks (NNs) and SVMs models. The experimental results reveal that the proposed models can result in much better reliability prediction performance than other technologies.

1. Introduction

The study concerned with reliability modeling and prediction in recent years gives clues of the solution of assessing the performance of engineering system [1,2]. With the development in computer technology, artificial intelligence techniques including neural networks (NNs) and support vector machines (SVMs) have been used for reliability prediction of many engineering areas.

NNs have become common methods in system reliability modeling, evaluation and prediction because they can approximate any nonlinear function with arbitrary accuracy. Liu et al. [3] demonstrated how multilayer perceptions NNs (MLPNNs) could successfully identify underlying failure distribution and estimate the parameters. A MLPNN based expert system was developed for evaluating power system reliability in Amjady and Ehsan [4]. Xu et al. [5] applied MLPNN and radial basis function NN (RBFNN) to predict engine system reliability and they found that NNs provide more accurate prediction results than the autoregressive (AR) model. Chang et al. [6] presented a hybrid learning neural fuzzy system to predict engine system reliability. Numerical results demonstrated that the proposed model was able to achieve more accurate prediction results than AR and NNs models. Ho et al. [7] suggested a comparative analysis of NNs and AR techniques in terms of their ability to predict failures of repairable systems. Experimental results showed that both recurrent NN and MLPNN outperformed the AR model in prediction accuracy. Although a large number of successful applications have shown that NNs have been successfully adopted in many prediction fields [3–7], NNs suffer from some weaknesses such as locally optimal solutions and over-fitting, which can make the prediction precision unsatisfactory.

Developed by Vapnik [8], SVMs have been widely applied to engine system's reliability prediction as well. Pai [9] employed the SVM model with genetic algorithm to predict system reliability and failures. The presented model provided lower predicting errors than the MLPNN, RBFNN and ARIMA model. Hong and Pai [10] suggested the SVM method to predict engine reliability, and the simulated results showed that the presented SVM model was a valid and promising alternative in reliability prediction. Chen [11] proposed a new prediction model to predict reliability in engine systems by using real-value genetic algorithm to search for SVM's optimal parameters. The experimental results demonstrated that the proposed model outperformed the existing NNs and AR models. Moura et al. [12] presented a comparative analysis in order to

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evaluate the effectiveness of the developed SVM model in predicting time-to-failure and reliability of engineered components based on time series data. The comparison showed that the performance of the proposed SVM model outperformed or was comparable to the RBFNN, MLPNN, ARIMA and the infinite impulse response locally recurrent neural network (IIR-LRNN) models.

Established on the structural risk minimization principle by minimizing an upper bound of the generalization error, SVM can result in resistance to the over-fitting problem [13]. However, SVM formulates the training process through quadratic programming, which can take much more time. In 1999, Suykens and his colleagues proposed a novel SVM known as least squares support vector machine (LSSVM) [14], which is able to solve linear problems quicker with a more straightforward approach. Until now, LSSVM has been successfully used in pattern recognition and nonlinear regression estimation problems [15–20]. A hybrid model based on artificial bee colony and LSSVM for commodities prices prediction was proposed in [15]. A heat rate prediction method based on online LSSVM, which possesses dynamic prediction functions, was presented by using the gravitational search algorithm to optimize the regularization parameter and the kernel parameter of the online LSSVM modeling in [16]. A new approach that combines the merits of the response surface method and the LSSVM for reliability analysis was suggested in [17]. Ekici [18] developed a LSSVM based intelligent model to predict the next day's solar isolation. An algorithm for machine condition prediction was proposed in [19] by jointly using LSSVR, genetic algorithm and cumulative sum method.

NNs and SVRs have desired characteristics such as optimal solution and generalization capability, but they do not have capacity to handle system uncertainty and stochastic nature [20,21]. Kalman filter can deal with system uncertainty and stochastic nature and is an alternative for online prediction. Therefore, we have proposed the nonlinear filters based LSSVM model for reliability and failures prediction of engine systems in this paper. The main contributions include three-fold. Firstly, two novel hybrid predictive modeling methods are developed by integrating the iterated extended Kalman filter (IEKF) [22] and the iterated unscented Kalman filter (IUKF) [23] with the LSSVM (they are shortened as the IEKF-based-LSSVM model and the IUKF-based-LSSVM model.) based nonlinear state-space model to enhance the capacity of handling stochastic and dynamic uncertainty as well as minimize the errors of reliability prediction. Secondly, the nonlinear state-space model is formed based on the LSSVM and then the IEKF and the IUKF are employed to conduct iterative state estimation on the LSSVM based nonlinear state-space model with strong stochastic uncertainty. Finally, the reliability data sequence is predicted from the IEKF-based-LSSVM and IUKF-based-LSSVM models, the integrated approaches can reduce prediction errors by well accounting for the stochastic and dynamic nature of reliability data sequence in this way.

The remainder of the article is organized as follows. In Section 2, LSSVM and iterated nonlinear filters are integrated to form the novel IEKF-based-LSSVM and IUKF-based-LSSVM models for reliability prediction. Illustrative examples from previous literatures based corresponding experimental results are provided and discussed in detail in Section 3. Section 4 concludes the paper with a discussion on future work.

2. Prediction model

2.1. A least square support vector machine based state-space model

In LSSVM a linear estimation is done in kernel induced feature space by considering a data set $\{\boldsymbol{u}_i, y_i\}$ $(i = 1, 2, \ldots, l)$ with input data $\boldsymbol{u}_i \in R^m$ and output data $y_i \in R$. When $\phi(\cdot)$ denotes the feature map the regression model can be constituted as [24]

$$y = \boldsymbol{\omega}^{\mathrm{T}} \cdot \phi(\boldsymbol{u}) + b, \tag{1}$$

where $\boldsymbol{\omega}$ is the weight vector of the target function and b is the bias term. As in SVM, it is necessary to minimize a cost function C containing a penalized regression error as shown below [25]

$$C = \frac{1}{2}\boldsymbol{\omega}^{\mathrm{T}} \cdot \boldsymbol{\omega} + \frac{1}{2}\gamma\sum_{i=1}^{l} e_i^2, \tag{2}$$

$$\text{s.t.} \quad y_i = \boldsymbol{\omega}^{\mathrm{T}} \cdot \phi(\boldsymbol{u}_i) + b + e_i \quad (i = 1, 2, \ldots, l), \tag{3}$$

where γ is the penalty factor and e_i $(i = 1, 2, \ldots, l)$ are training errors. This convex optimization problem can be solved by using the Lagrange multipliers method [26]

$$L(\boldsymbol{\omega}, b, e, \alpha) = \frac{1}{2}\|\boldsymbol{\omega}\|^2 + \gamma\sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l}\alpha_i\{\boldsymbol{\omega}^{\mathrm{T}}\phi(\boldsymbol{u}_i) + b + e_i - y_i\} \tag{4}$$

where α_i $(i = 1, 2, \ldots, l)$ are Lagrange multipliers. To obtain the optimum solution of Eq. (4), all corresponding partial first derivatives are set to zero and then can obtain [20]

$$\frac{\partial L}{\partial \boldsymbol{\omega}} = 0 \rightarrow \boldsymbol{\omega} = \sum_{i=1}^{l}\alpha_i\phi(\boldsymbol{u}_i), \tag{5}$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l}\alpha_i = 0, \tag{6}$$

$$\frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma e_i \quad (i = 1, 2, \ldots, l), \tag{7}$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \boldsymbol{\omega}^{\mathrm{T}}\phi(\boldsymbol{u}_i) + b + e_i - y_i = \gamma e_i \quad (i = 1, 2, \ldots, l). \tag{8}$$

Let

$$K(\boldsymbol{u}_i, \boldsymbol{u}_j) = \phi(\boldsymbol{u}_i)^{\mathrm{T}} \cdot \phi(\boldsymbol{u}_j). \tag{9}$$

Putting Eq. (9) into Eq. (1), the following result can be obtained [25]

$$y = h(\boldsymbol{\alpha}, b, \boldsymbol{u}) = \sum_{i=1}^{l}\alpha_i K(\boldsymbol{u}_i, \boldsymbol{u}) + b. \tag{10}$$

In this work, LSSVM is performed with radial basis function (RBF) as a kernel function and it is defined as

$$K(\boldsymbol{u}_i, \boldsymbol{u}_j) = \exp\left(\frac{-\left\|\boldsymbol{u}_i - \boldsymbol{u}_j\right\|^2}{2\delta^2}\right) \quad (i, j = 1, 2, \ldots, l), \tag{11}$$

where δ is an adjustable parameter to determine the RBF kernel width. Following from solving a set of linear equations [20], the vector which consists of the vector $\boldsymbol{\alpha}$ and the bias term b can be given as below

$$\begin{bmatrix} 0 & \mathbf{1}l\mathrm{T} \\ \mathbf{1}l & \boldsymbol{K} + \gamma^{-1}\boldsymbol{I} \end{bmatrix} \times \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}, \tag{12}$$

where $\boldsymbol{K}$ denotes the kernel matrix with ijth element in Eq. (9) and $\boldsymbol{I}$ denotes the identity matrix $l \times l$, $\mathbf{1}l = [1 \quad 1 \quad 1 \quad \cdots \quad 1]^{\mathrm{T}}$. Hence, the solution is

$$\begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{1}l\mathrm{T} \\ \mathbf{1}l & \boldsymbol{K} + \gamma^{-1}\boldsymbol{I} \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}, \tag{13}$$