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Application of Wavelet Thresholding Filter to Improve Multi-Step Ahead Prediction Model For Hydraulic System

Javad Safehian[1,a], Alireza Akbarzadeh[2,b] and Behnam Motakef Imani [3,c]

[1,2,3] Center for Applied Research on Soft Computing and Intelligent Systems (CARSIS), Mechanical Engineering Department, Ferdowsi University of Mashhad, Mashhad, Iran

[a] safehian.javad@gmail.com , [b] ali_akbarzadeh_t@yahoo.com, [c] bm_imani@yahoo.com

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Abstract. Proper operation of a hydraulic system used in a fatigue test machine (FTM) is crucial. This is because a fatigue test may take well over hours and is not necessarily supervised. Any system failure may result in specimen destruction or experiment failure. In this study experimental data is collected and analyzed to prognoses the hydraulic system. Prognosis may be used to set an alarm level when the predicted values of failure fall within the warning region. This paper presents an approach to predict the operating conditions of a hydraulic system a few increments ahead in time, otherwise known as multi-step ahead (MS). The approach is further validated using experimental data. To do this, applied force on standard aluminum specimen is recorded in time series. Wavelet soft thresholding is used to filter and reduce the effect of noise and sharp edges in the measured applied force data (time series). Embedding dimension and time delay are determined using Cao's method and auto mutual information (AMI) technique, respectively. These values are subsequently utilized as inputs for constructing prediction models to forecast the future values of the machines' operating conditions. The results show that the neural network (NN) prediction model can track the change in machine conditions and has the potential to be used as a machine fault prognosis tool.

Introduction

Condition based maintenance (CBM) is one type of preventive maintenance strategy which can be broadly classified into three categories: experience-based, model based, and data-driven based. In previous studies, data-driven prognosis approach using one-step ahead (OS) and multi-step ahead (MS) prediction methodologies are proposed for forecasting machines operating conditions [1] & [2]. However, denoising of the data was not considered. Wavelet transforms is a denoising tool which provides useful decompositions of main time series. The transformed wavelet data improves the ability of a forecasting model by capturing useful information on various resolution levels [3]. In wavelet decomposition, high-pass filters act as averaging filters and low-pass filters produce details. Wavelet coefficients correspond to details and when the details are small; they might be considered as noise and therefore excluded [4]. To remedy this problem, avoid excluding data that may be significant, wavelet thresholding may be used. In this study, NN is applied to construct prediction model .The main problems with MS prediction model (NN) are the number of initial observations that should be used as the inputs for prediction model and the number of steps used by the prediction model to obtain the best performance. The first and second problems can be solved using the Cao's method [5] & [6] and auto mutual information (AMI) [7], respectively. Finally the constructed prediction model is used to prognosis operating conditions of a hydraulic system by collecting and analyzing the experimental data. Wavelet is used in prediction of a chemical process monitoring [8] and is proposed for wind speed and power output prediction of two wind farm [9].

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Background knowledge

Wavelet. The wavelet transform is capable of providing time and frequency information simultaneously. Wavelet transform provides useful decompositions of main time series, so that wavelet-transformed data improve the ability of a forecasting model by capturing useful information on various resolution levels [3]. The comparison of different thresholding techniques (Universal thresholding, Mini-max estimation and Stein's Unbiased Risk Estimate (SURE) thresholding [10]) show that the universal thresholding technique with Daubechies wavelet (db3) is more effective. It is therefore, recommended to be adopted for data series filtering (time series smoothing). The procedure of wavelet filtering is illustrated in Fig. 1.

Fig. 1. Time series filtering procedures using wavelet thresholding

Multi-step-ahead. For a dynamic system, a scalar output at any point in time can be predicted by a function involving time-delayed versions of the same output. The following relationship holds for dynamic systems if $l > 2d$, where d is the dimension of the state space dynamics [11]:

$$y(t) = F[y(t-\tau), y(t-2\tau), \dots, y(t-l\tau)]. \quad (1)$$

where, τ is the sampling time (time delay), y(t + τ) is the forecasted values, y(t),y(t - τ),...,y(t-m τ) are the current and past observed values and l is the number of inputs (embedding dimension) for the model . The optimal time delay is determined by the first local minimum of the AMI of time series. In Cao method, $E1(m)$ stops changing when embedding dimension is greater than some value m_0. Therefore, m_0 is the minimum desired embedding dimension. Considering the multi-step-ahead forecasting methods, two model structures are proposed: The first structure, as shown in Fig. 2-A, uses the same NN (Model 1) for all sequential time steps. The second structure, as shown in Fig. 2-B, uses a different NN (Models 1,2 and 3) for each time step. Each network has one output which represents the forecast for its time step. In the present paper, the second structure is adopted.

The proposed predicting method. The proposed method for prognosis of hydraulic operation condition in this paper is comprised of five steps as: Data acquisition, Data filtering, Data dividing, Training–validating and finally Predicting. Relation of these steps is shown in Fig. 4.

Experiment

The proposed method is applied to prognosis of a hydraulic system used as a Fatigue test machine (FTM). Applied force on specimen are recorded by load cell which makes a trending data (time series) of a fatigue test machine condition. FTM is shown in Fig. 3.

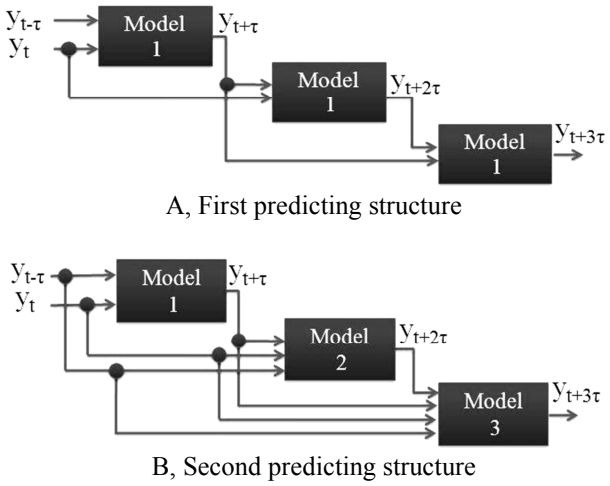

Fig. 2. Proposed MS predicting structure

Fig. 3. Fatigue test machine

In certain cases, testing process may take long hours. Therefore, some faults may gradually occur which negatively effects material testing process. As a case study, standard aluminum specimen is selected. In this paper, relief valve setting is manually and gradually changed to create a fault. This fault effects servo valve operation and therefore maximum and mean of the applied force on the specimen. The test is run for 1.5 hours. Data acquisition records approximately 2.8×10^6 data samples. See Fig. 5. The universal thresholding method with Daubechies wavelet (db3) is adopted for measured data series filtering (time series smoothing). Comparison of original and de-noised time series is shown in Fig. 6. Fig. 7 is used to obtain the optimal time delay which is found to be $\tau = 11$. Similarly from Fig. 8, the embedding dimension l is chosen as $l = 7$. Table-1 shows computed time delay and embedding dimension for the original and de-noised signals. As shown in Table-1, it is observed that denoising time series causes longer prediction (bigger time delay) and lower input (embedding dimension) than the original signal. Therefore, the de-noised signal is selected for the NN training.

Table 1. Time delay and embedding dimension for original and de-noises signals

	Time delay (τ)	*Embedding dimension (l)*
Original Signal	*3*	*7*
De-noised Signal	*11*	*5*

Upon computing the time delay and the embedding dimension, the process of constructing the prediction models is established by NN. Back-propagation training method is used to train NN. In this paper number of neurons in the second layer (first hidden layer) and the third layer (second hidden layer) are 20 and 25 respectively. Fig. 9 and Table-2 show the performance of predicting model. As shown, the NN output predicts the actual output of the de-noised system.

Table 2. The RMSEs (Root Mean Square Error) [2] of prediction model

Data type	*Training*	*Testing*
Original signal	*0.068014*	*0.2549*
De-noised signal	*0.019548*	*0.08958*

Conclusion

In this paper a method for multi-step ahead prediction prognosis is presented. Wavelet thresholding technique is utilized to eliminate random noise and outliers from the signal. Time delay and embedding dimension of the de-noised signal is calculated. Neural network is used to construct the MS prediction model. A hydraulic system of a fatigue test machine is selected to validate the MS prediction model. A specimen is selected and test is ran for 1.5 hours and using a data acquisition system experimental data, force of a load cell, is collected. A relief valve setting is manually changed to create a fault on the performance of the hydraulic servo valve The Multi-step ahead prediction prognosis method presented in this paper is applied. It is shown that the prediction model is successful in detecting the actual fault symptom of the system.

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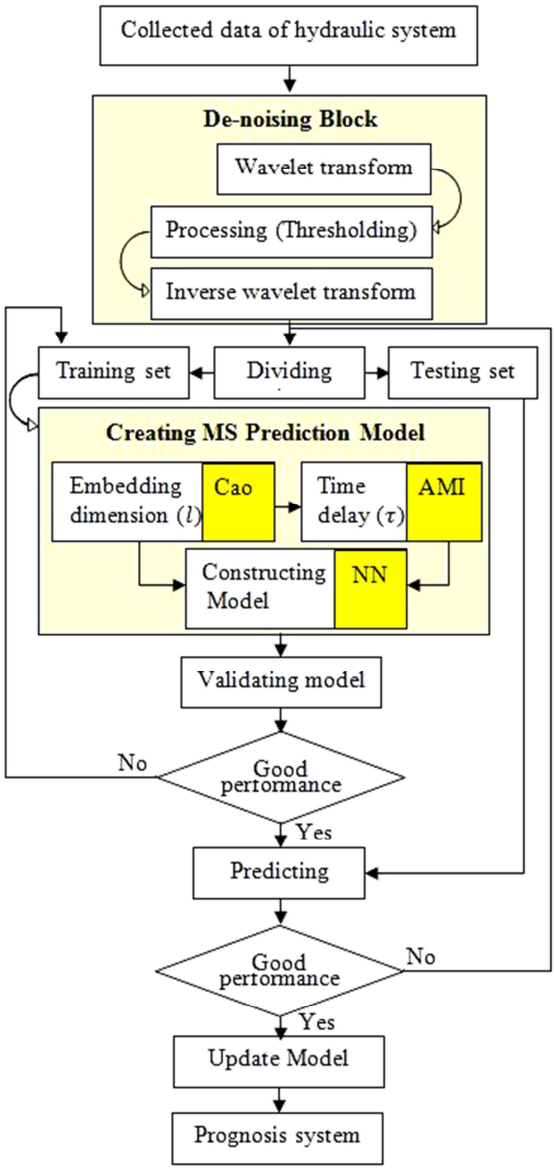

Fig. 4. MS prediction model flow chart

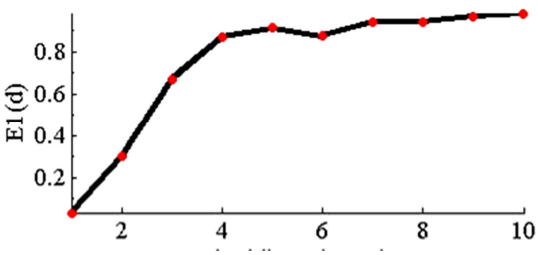

Fig. 8. Embedding dimension ($l = 7$)

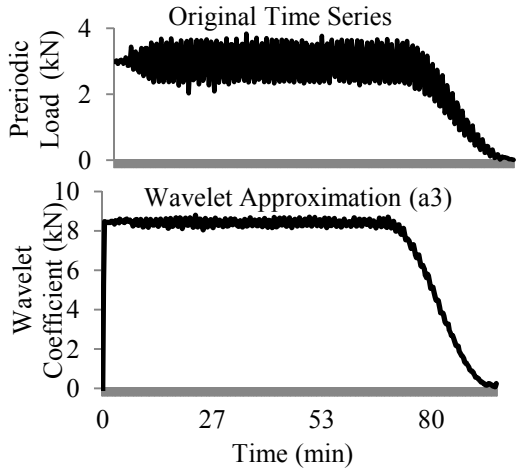

Fig. 5.Original signal and wavelet approximation for recorded force series using Daubechies filter of order 3

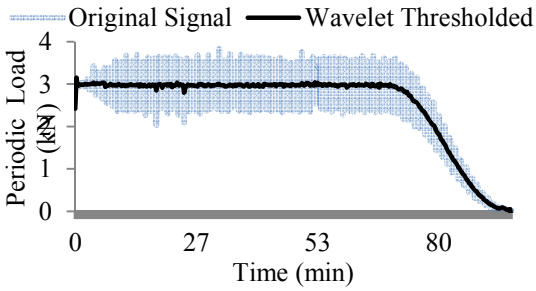

Fig. 6. Original and filtered (universal thresholding methods) recorded load cell values as time series

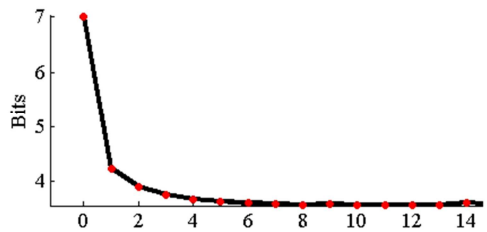

Fig. 7. Time delay estimation (τ=11)

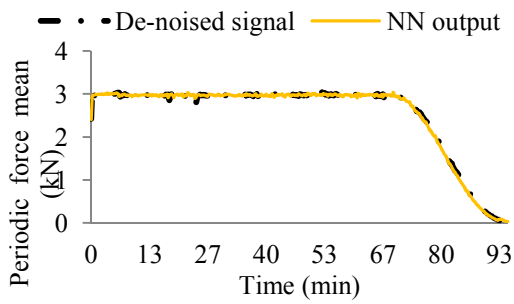

Fig. 9. Predicted and actual de-noised data

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