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Mechanical Systems and Signal Processing 21 (2007) 809–823
Mechanical Systems and Signal Processing
www.elsevier.com/locate/jnlabr/ymssp

An adaptive predictor for dynamic system forecasting

Wilson Wang*

Department of Mechanical Engineering, Lakehead University, 955 Oliver Road, Thunder Bay, Ontario, Canada P7B 5E1

Received 23 July 2005; received in revised form 11 December 2005; accepted 14 December 2005
Available online 8 February 2006

Abstract

A reliable and real-time predictor is very useful to a wide array of industries to forecast the behaviour of dynamic systems. In this paper, an adaptive predictor is developed based on the neuro-fuzzy approach to dynamic system forecasting. An adaptive training technique is proposed to improve forecasting performance, accommodate different operation conditions, and prevent possible trapping due to local minima. The viability of the developed predictor is evaluated by using both gear system condition monitoring and material fatigue testing. The investigation results show that the developed adaptive predictor is a reliable and robust forecasting tool. It can capture the system's dynamic behaviour quickly and track the system's characteristics accurately. Its performance is superior to other classical forecasting schemes.

Keywords: Neuro-fuzzy forecasting scheme; Adaptive training; Machinery condition monitoring; Model uncertainty; Fatigue testing

1. Introduction

A reliable predictor is very useful to a wide range of industries to forecast the upcoming states of a dynamic system. In mechanical systems, for example, the forecasting information can be used for: (1) condition monitoring to provide an accurate alarm before a fault reaches critical levels so as to prevent machinery performance degradation, malfunction, or catastrophic failure; (2) scheduling of repairs and predictive/preventive maintenance in manufacturing facilities; and (3) predictive and fault-tolerant control. System state forecasting utilises available observations to predict the future states of a dynamic system. The observations can be patterns from such information carriers as temperature, acoustic signal, or vibration. The vibration-based approach, however, is the most commonly used technique because of the ease of measurement and analysis. Thus, it is also used in this study.

Time-series forecasting can be performed for one-step or multiple-step predictions. The more steps, the less reliable the forecasting operation is because the involved approaches in the multiple-step prediction are associated with one-step operations. Thus, this research also focuses on one-step forecasting operations.

Several techniques have been proposed in the literature for time-series prediction. The classical approaches are the use of stochastic models [1] and dynamics-based techniques [2,3]; usually, these methods are easy to implement but difficult in forecasting the behaviour of complex dynamic systems. Recent interest in time-series

*Tel.: +1 807 766 7174; fax: +1 807 343 8928.
E-mail address: Wilson.Wang@Lakeheadu.ca.

0888-3270/$ - see front matter
doi:10.1016/j.ymssp.2005.12.008

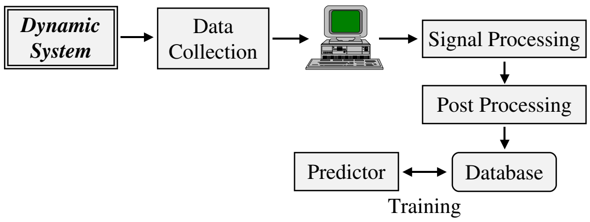

Fig. 1. The architecture of the forecasting tool based on the adaptive predictor.

forecasting has focused on the use of flexible models such as neural networks (NNs). After being properly trained, NNs can represent the non-linear relationship between the previous states and the future states of a dynamic system [4]. NN-based predictors have two typical network architectures: feedforward and recurrent networks, both of which have been employed in some applications [5,6]. Advanced investigation has indicated that the recurrent network predictors perform superior to those based on the feedforward networks [7]. NN forecasting schemes, however, have some disadvantages: Their forecasting operation is opaque to users, and the convergence of training is usually slow and not guaranteed. To solve these problems, synergetic schemes based on NNs and fuzzy logic have been adopted in time-series forecasting [8]. In such synergetic schemes, the fuzzy logic provides NNs with a structural framework with high-level if-then rule-based thinking and reasoning, whereas the NNs provide the fuzzy systems with learning capability [9,10]. Jang et al. [11] proposed a neuro-fuzzy (NF) scheme for time-series forecasting. By simulation, they found that the NF predictor performed better than both the stochastic models and the feedforward NNs. The author and his research team developed an NF prognostic system for machinery condition applications [12]. Their investigation indicated that if an NF predictor is properly trained, it performs even better than both the feedforward and the recurrent network forecasting schemes.

Even though the NF predictors have demonstrated their superior properties to other classical time-series forecasting schemes, advanced research needs to be done in a few aspects before they can be applied to general real-time industrial applications [13]: (1) improving their application robustness to accommodate different system conditions; (2) mitigating the requirements for the representative data sets; and (3) improving their convergence properties, especially for complex operation applications. Consequently, the aim of this paper is to develop an adaptive predictor to solve these problems in order to provide industries with a more reliable and real-time forecasting tool. Fig. 1 schematically shows the architecture of the forecasting tool based on the proposed adaptive predictor. Signals are collected using corresponding sensors. After being properly filtered and sampled, the signals are fed into a computer. In further processing, the first step is to generate the representative features from the collected signals by applying different signal processing techniques. Post-processing is done to enhance the feature characteristics and derive monitoring indices for forecasting operations. All the involved signal processing techniques and forecasting schemes are coded in MATLAB and then translated to a C++ environment for general application purposes.

This presentation starts with a description of the adaptive predictor and the corresponding adaptive training technique. Next, the predictor is implemented for real-time monitoring applications. The viability of this new predictor is verified by online experimental tests related to gear condition monitoring and material fatigue testing.

2. The adaptive NF predictor

In this proposed adaptive predictor, the forecasting reasoning is performed by fuzzy logic, whereas the fuzzy system parameters are trained by using NNs. To make it compatible with those in the author's prior work [12], four input variables $\{x_{-3r}\ x_{-2r}\ x_{-r}\ x_0\}$ are utilised in this case, where x_0 represents the current state of the dynamic system and r denotes the time step. If two membership functions (MFs), *small* and *large*, are assigned to each input variable, then $2^4 = 16$ rules will be formulated to predict the future state of a dynamic system, x_{+r},

$$\Re_j : \text{If } (x_0 \text{ is } M_0^j) \text{ and } (x_{-r} \text{ is } M_1^j) \text{ and } (x_{-2r} \text{ is } M_2^j) \text{ and } (x_{-3r} \text{ is } M_3^j) \text{ then } x_{+r} = C_j, \tag{1}$$

where $C_j = c_0^j x_0 + c_1^j x_{-r} + c_2^j x_{-2r} + c_3^j x_{-3r} + c_4^j$; M_i^j denote MFs; c_i^j are constants; $i = 0,1,\ldots,3$, $j = 1,2,\ldots,16$.