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BJEST: A reverse algorithm for the real-time predictive maintenance system

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Abstract

An algorithm, to estimate the machine system parameters from the motion current signature, based upon non-linear time series techniques for use in the real-time predictive maintenance system is presented in this paper. Earlier work has introduced the use of a neural-network approach to learn non-linear mapping functions for condition monitoring systems. However, the performance of the neural-network largely depends upon the quality of the training data, and that of the quality and type of the pre-processing of the input data. A reverse algorithm called BJEST (Bansal–Jones Estimation), for estimating the machine input parameters using the motion current signature, has been designed and proven to be successful in estimating the macro-dynamics of the motion current signature. This motivated the enhancement of the predictive analysis to incorporate non-linear characteristic of the motion current signature. The results show considerable improvement in the estimation of the parameters using the enhanced BJEST algorithm due to estimation consistency, hence, improving the real-time predictive maintenance system.

Keywords: Neural-network; Motion current signature; Machine parameter; Predictive maintenance; Non-linear time series; Surrogate data test

1. Introduction

Growing complexity of industrial manufacturing and the need for higher efficiency, greater flexibility, better product quality and lower cost have changed the face of the manufacturing practice. The need for efficiency and maximum production time creates a requirement for high reliability supported by an effective maintenance system. Functions such as maintenance that are seen as being 'non-value adding' are being continuously required to reduce costs, whilst keeping equipment running in an optimum condition. Effective monitoring can support cost reduction and efficiency improvement strategies [1]. Modern machines typically use some form of direct current (DC) motor for motion dynamics and the process described is based upon such motors. Earlier work has introduced an effective, real-time, predictive maintenance system based on the motion current signature using a neural-network approach [2,3]. The aim of the system is to localize and detect abnormal electrical conditions in order to predict mechanical abnormalities. One of the fundamental requirements for the successful application of a neural-network is the availability of relevant, information-rich training data. While an ideal solution would be to utilize training data collected from a real production system, it is impractical to scan the entire range of machine operations [2]. Thus, the use of a simulation model for generating the training data, covering harder to replicate machine conditions, like current limit over-run, was motivated [2]. A simulation model, TuneLearn,[1] of a closed-loop form based on a PID controller was developed and shown to be capable of mapping the motion current signature to the system parameters [3]. Whilst validating the simulation model, a reverse algorithm called BJEST (Bansal–Jones Estimation), for estimating the machine input parameters using the motion current signature, was designed and proven to be successful in estimating the macro-dynamics of the motion

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[1] The simulation model developed as part of joint University and Rockwell Automation research programme.

current signature [3]. Also, the performance of the neural-network largely depends upon a number of factors including:

(1) the quality of the training data;
(2) quality and type of the pre-processing of the input data;
(3) the type of the neural-network technique adopted;
(4) the training methodology used.

The success in estimating the macro-dynamics of the motion current signature using BJEST, referred to as the reverse algorithm here onwards, and the dependence of the performance of a neural-network approach upon training data, motivated the enhancement of the reverse algorithm to incorporate non-linear characteristic. This paper details the enhancements performed to the reverse algorithm to incorporate the non-linear characteristics of the motion current signature. However, the first step is to statistically test the motion current signature for non-linearity, which has been performed using surrogate data testing.

The remainder of this paper is organized as follows: Section 2 discusses the surrogate data test as a means for testing for non-linearity in the motion current signature; Section 3 provides the results of the surrogate data testing; Section 4 describes the enhanced version of the reverse algorithm, which integrates non-linear noise reduction techniques to improve estimation performance; Section 5 provides the comparison of the performance of the new enhanced reverse algorithm against the linear reverser algorithm described in [3]; and Section 6 gives the conclusions.

2. Testing for non-linearity: surrogate data test

The surrogate data testing is a method used to test for non-linearity in the data [7]. The motivations for pursuing this avenue of research are:

(1) The simulation model, which was based upon the linear modelling techniques, has failed to replicate the micro-dynamics of the motion current signature [3];
(2) Prior knowledge regarding the motion current signature and the effect of higher order factors, such as friction and backlash, indicate the presence of non-linearity.

Nevertheless, the reasons given above can prove insufficient to justify the use of non-linear techniques for analyzing motion current signature. The fact that a system contains non-linear components does not prove that this non-linearity is also reflected in a specific signal measured from that system. Due to these reasons, formal validation of the presence of non-linearity is desirable.

The simplest way to test for non-linearity is to calculate some general measure of non-linearity or chaos, examples being various high-order statistics and Lyapunov exponents [4]. One popular method has been to calculate both the correlation dimension and first Lyapunov exponent—a combination of convergence of the correlation dimension and a positive exponent was then taken as an indication of non-linearity [5]. However, it is now generally accepted that measures such as these are not sufficient, by themselves, to establish chaotic or non-linear behavior in the data [6,7]. In particular, the measurement of such statistics is often prone to noise contamination and requires large input data sets, which increases the computational overhead. In addition, using longer data sets increases the likelihood of encountering non-stationarities. Errors associated with the acquisition of data such as inappropriate sampling frequency, noise filtering and digitization error can all lead to erroneous values of these statistics being returned. Finally, even if we were able to determine these values with sufficient accuracy, the actual distribution for the non-linear statistic in question is generally not known except for the simplest of models.

The method of surrogate data analysis [7] solves some of these problems by providing a suitable statistical framework in which non-linearity tests may be performed more reliably. It is based on the principle of Monte Carlo methods: the idea is to sample in the space of possible time series matching some carefully chosen null hypothesis, then perform a standard statistical t-test to reject this hypothesis. The first step is to specify a null hypothesis against which the non-linearity of the data is tested. Hypothesis testing [8] is a method used in the statistical analysis to state the alternative (for or against the hypothesis), which minimizes certain risks. Essentially, an assumption about the data, known as the null hypothesis (H_0), which is expected to contradict, is made.

The observed dynamical system could fall into one of the four categories:

(1) linear deterministic (e.g. Newtonian, undamped pendulum, sinewave);
(2) non-linear deterministic (e.g. Lorenz, Henon map);
(3) linear stochastic (e.g. a linear Markov model);
(4) non-linear stochastic (e.g. a non-linear Markov model).

In this paper, the null hypothesis, H_0, for motion current signature is that the observed data is an element of a linear stochastic Gaussian process. After the null hypothesis is identified, a non-linear parameter is extracted from the data. In theory, this can be anything, provided it is able to reject data not belonging to the class of models defined by the null hypothesis. Lyapunov exponents and correlation dimensions have been popular choices [9]. The most important requirement when choosing this parameter, however, is that it should have a relatively localized distribution when applied to data that conforms to the null hypothesis. In other words, the value of this quantity should be sensitive to changes near regions of interest since this will increase the ability to reject data with different characteristics from the null hypothesis.