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Technical Note

An experiment of state estimation for predictive maintenance using Kalman filter on a DC motor

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Abstract

Preventive maintenance (PM) is an effective approach to promoting reliability. Time-based and condition-based maintenance are two major approaches for PM. No matter which approach is adopted for PM, whether a failure can be early detected or even predicted is the key point. This paper presents the experimental results of a failure prediction method for preventive maintenance by state estimation using the Kalman filter on a DC motor. The rotating speed of the motor was uninterruptedly measured and recorded every 5 min from 1 April until 20 June 2001. The measured data are used to execute Kalman prediction and to verify the prediction accuracy. The resultant prediction errors are acceptable. Futhermore, the shorter the increment time for every step used in Kalman prediction, the higher prediction accuracy it achieves. Failure can be prevented in time so as to promote reliability by state estimation for predictive maintenance using the Kalman filter. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Kalman filter; State estimation; Failure prediction; Preventive maintenance; DC motor

1. Introduction

High quality and excellent performance of a system are always goals for engineers to achieve. Reliability engineering integrates quality and performance from the beginning to the end of a system life [1]. Therefore, reliability can be treated as the time dimensional quality of a system. Reliability is affected by every stage throughout the system life, including its development, design, production, quality control, shipping, installation, operation, and maintenance. Consequently, paying attention to each of the stages can promote reliability. Specifically, in the onsite operation phase, failures are the main causes that worsen performance and degrade reliability. Accordingly, failure avoidance is the main approach to reliability assurance. There are three main types of maintenance, namely improvement maintenance (IM), preventive maintenance (PM), and corrective maintenance (CM) [2]. The efforts of IM are to reduce or eliminate entirely the need for maintenance, i.e. IM is performed at the design phase of a system emphasizing elimination of failures that require maintenance. There are many restrictions for a designer, however, such as space, budget, market requirements, etc. Usually, the reliability of a product is related to its price. By contrast, CM is the repair actions executed after failure occurrence. PM denotes all actions intended to keep equipment in good operating condition and to avoid failures [2]. As a result, PM should be able to pinpoint when a failure is about to occur, so that repair can be performed before such failure causes damage.

PM is an effective approach to promoting reliability [3]. Time-based and condition-based maintenance are two major approaches for PM. No matter which approach is adopted for PM, whether a failure can be early detected or even predicted is the key point. If a device is judged to know that it is going to fail by the predicted future state variables, the failure can be prevented in time by PM. However, future state variables should be accurately predicted at a reasonably long time ahead of failure occurrence [4,5]. A failure prediction study entitled 'State estimation for predictive maintenance using Kalman filter' has been proposed [6]. In the study, failure times were generated by Monte Carlo simulation and predicted by the Kalman filter. One-step-ahead and two-step-ahead predictions were conducted. Resultant prediction errors are sufficiently small in both predictions. Even so, the failure prediction was simulated on a computer after all. In the current study, a DC motor and a data acquisition system are set to implement the simulation. The rotating speed of the motor is chosen as the major state variable to judge whether the motor is going to fail by state estimation using the Kalman filter. The rotating speed of the motor was uninterruptedly measured and recorded

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Nomenclature

$(\cdot)_k$	The value of $(\cdot)$ at time kT
$(\hat{\cdot})_{a/b}$	The estimate of $(\cdot)$ at time aT based on all known information about the process up to time bT
A	A matrix
A_c	Coefficient matrix of the state equation for a continuous system
A_d	Coefficient matrix of the state equation for a discrete system
A^T	Transpose matrix of A
A^{-1}	Inverse matrix of A
B	Damping coefficient
B_c	Coefficient matrix of the state equation for a continuous system
B_d	Coefficient matrix of the state equation for a discrete system
B_k	Coefficient matrix for the input term of a discrete state equation
C	A matrix
C_c	Coefficient matrix of the state equation for a continuous system
C_d	Coefficient matrix of the state equation for a discrete system
D_c	Coefficient matrix of the state equation for a continuous system
D_d	Coefficient matrix of the state equation for a discrete system
E	Applied voltage
E_r	Estimation error
H_k	Matrix giving the ideal (noiseless) connection between the measurement and the state vector
i_a	Armature winding current
J	Moment of inertia of rotor and load
k_b	Back emf constant
K_k	Kalman gain
k_T	Motor torque constant
L_a	Armature winding inductance
L^{-1}	The inverse Laplace transform
$P_{k/k-1}$	Estimation error covariance matrix
Q_k	Covariance matrices for disturbance
R	Armature winding resistance
R_k	Covariance matrices for noise
t	Time variable
T	Motor output torque
T	Increment time for every step in Kalman prediction
U_k	Control input of a discrete state equation at state k
V	Variation of the estimated rotating speed
V_k	Noise, measurement error vector. It is assumed to be a white sequence with known covariance
W_k	Disturbance, system stochastic input vector. It is assumed to be a white sequence with known covariance and having zero cross-correlation with V_k sequence
x, X	Variable of a distribution function
X_{D0}	Initial states resulting from deterministic input
X_k	System state vector at state k
X_{S0}	Initial states resulting from stochastic input
Y_k	System output vector at state k
Z_k	Output measurement vector
θ	Motor angle displacement
$\dot{\theta}$	Motor rotating speed
μ	Mean value of a distribution function
σ	Standard deviation of a distribution function
Φ_k	Matrix relating X_k to X_{k+1} in the absence of a forcing function. It is the state transition matrix if X_k is sampled from a continuous process

every 5 min from 1 April until 20 June 2001. Instead of simulated data, the measured data are used to execute Kalman prediction and to verify the prediction accuracy in the current study.

In the next section, equations for state estimation of the Kalman filter are briefly introduced. Section 3 presents the transfer function, continuous state model, and the discrete state model of a DC motor that is employed in this paper. Section 4 presents the experiment setup with related parameters. Results and discussions are in Section 5.

2. Kalman filtering

The block diagram of a discrete system is shown in Fig. 1. The state equations [7] are:

$$X_{k+1} = \Phi_k X_k + B_k U_k + W_k, \tag{1}$$

$$Y_k = H_k X_k, \tag{2}$$

$$Z_k = Y_k + V_k. \tag{3}$$

State estimation aims to guess the value of X_k by using measured data, i.e. Z_0, Z_1, … Z_{k-1}. Let $a \geq b$, and define the notation $(\hat{\cdot})_{a/b}$ as the estimate of $(\cdot)$ at time aT based on all known information about the process up to time bT. Accordingly, $\hat{X}_{k/k-1}$ is called the prior estimate of X, and $\hat{X}_{k/k}$ is called the posterior estimate of X [8].

The Kalman filter is a copy of the original system and is driven by the estimation error and the deterministic input. The block diagram of the filter structure is shown in Fig. 2. The filter is used to improve the prior estimate to be the posterior estimate by the measurement Z_k. A linear blending of the noisy measurement and the prior estimate is written as given in Ref. [8]

$$\hat{X}_{k/k} = \hat{X}_{k/k-1} + K_k(Z_k - H_k \hat{X}_{k/k-1}), \tag{4}$$

where K_k is a blending factor for this structure. As depicted

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