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Condition-based Maintenance: Model vs. Statistics A Performance Comparison

Marc Engeler*[a], Daniel Treyer[b], David Zogg[b], Konrad Wegener[a], Andreas Kunz[a]

[a]ETH Zurich, 8092 Zurich - Switzerland
[b]FHNW, Hochschule für Technik, 5210 Windisch - Switzerland

* Corresponding author. Tel.: +41 (0)41 854 52 86; fax: +41 (0)41 854 52 30. *E-mail address:* engelerm@student.ethz.ch

Abstract

The current development in industrial applications shows a variety of approaches to perform maintenance: With reactive maintenance, only parts which fail will be replaced. This causes high costs and high unexpected failure rates. Preventive maintenance uses a predefined service plan and also a wear part exchange schedule. The plan or schedule is often based on real-time or an operation time. This often results in fixed maintenance cycles or an operation time-based maintenance. This can lead to a replacement or maintenance of a completely healthy component or to ignoring components that need to be replaced more frequently. Condition-based maintenance is an advanced approach which is based on measured component data to identify the current status of a component. This status is used to determine the date of maintenance or exchange as estimated end of life. Thus, only damaged components are maintained or exchanged. The scope of this paper is to implement a model-based maintenance algorithm in a real industrial application to determine the remaining lifetime of a component. A very important requirement is a good identification process for the model and the component. However, short commissioning times and a variety of different components pose an increased effort to identify the parameters. Thus, this paper presents an approach for a parameter identification which solely relies on data being present in the numerical control of the machine. The model-based approach is then compared to a simpler statistical approach using data from a running production machine.

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Keywords: Industrie 4.0, Predictive Maintenance, Model Based Maintenance, Condition Monitoring

1. Introduction

The current development in industrial applications shows a variety of different approaches to maintenance. All approaches from purely reaction driven maintenance to condition-based maintenance represent an important cost and time factor during machine operation.

Today, maintenance is conducted in planned intervals to maximize uptime and production efficiency. However, these intervals only take into account a very conservative lifetime estimate, based on worst case experiences, although the exact load case, mounting configuration, the load on the bearings, improper use, and further lifetime enhancing or shortening conditions are not considered. Another problem is improper usage of components which can lead to a very short lifetime. Thus, poor communication of user errors (such as crashes, bad handling, etc.) can lead to unexpected downtimes which can severely hinder the production. To overcome the issue of complete ignorance of the current machine condition, a live monitoring to support condition-based maintenance is key for future production lines to reduce machine downtimes, which can span up to several days when an unwanted error occurs in a difficult component.

A first approach to condition-based maintenance for an electrical spindle is introduced in this paper, using a real-world example. The scope of this work is to implement a model-based algorithm in a real industrial application to determine the remaining lifetime of a component. Thus, it is crucial to have a good identification process for the model and the component. Identifying the models parameters of different components using external measurement devices pose an increased workload and thus would not be feasible. The goal of this work is to present an approach to parameter identification which solely relies on status data, present on the numerical control of the machine. State-of-the-art motor controllers contain a set of data (current, voltage, position) which allow a parameter identification to be conducted online, without any further effort. The resulting lifetime extrapolation can be conducted using an extrapolation of the identified parameters.

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2. Motivation

There are many approaches to condition monitoring of spindle drives and synchronous machines, such as the frequency response methods presented by [1] and [2], or various parameter identification methods as presented by [3].

However, these methods rely on a large set of data, usually measured under laboratory conditions. Since a standard industry application should be used in this paper, the goal is to get the necessary information without additional sensors, but to use data form the machine control instead. This allows identifying the component when it is already built into the machine. Without a complicated test procedure the parameter identification will be run during commissioning and with some experience from former application cases.

A first approach in this work is an overall identification of the full system using a third-order model with seven unknown parameters. Batch algorithms, such as least squares and prediction error methods as presented in [4] were used in a first step. Using standard process trajectories, these processes yielded bad conditioning and poor performance. To overcome these problems, an adequate excitation had to be considered. However, the complexity of the model made it hard to define an useful trajectory for the identification process.

To reduce the number of parameters for the identification step, the system was divided into several subsystems. For each subsystem a specific excitation signal is used. The excitation signal is based on a physical analysis of the differential equations (1) and (2). With these excitation signals, a simplification of the model and the identification algorithm was achieved, which will be described in this paper.

A second approach is a purely statistical algorithm based on the measured data. This purely mathematical approach does not allow further insight into the resulting data, can however be run in parallel to the normal machine operation and does not require special excitation signals.

The condition estimation, which will be described in the end can be applied to both approaches and is the basis of a condition-based maintenance. The two approaches each offer unique benefits which will be presented in the concluding words.

3. Model of a Spindle Drive

In literature, there are several approaches to model a synchronous drive, which range from detailed models of magnetic flux as presented by [5] to simple models as presented by [6]. The model used in this work is based on the simple model with some further additions.

3.1. Electrical Model

The electrical model, as presented by [6] is shown in (1) and (2).

$$L_s \frac{\mathrm{d}I_d(t)}{\mathrm{dt}} = U_{sd} - RI_d + pL_s\omega_m I_q \quad (1)$$

$$L_s \frac{\mathrm{d}I_q(t)}{\mathrm{dt}} = U_{sq} - RI_q - pL_s\omega_m I_d - \frac{3}{2}p\omega_m\Psi_0 \quad (2)$$

The electrical parameters consist of L_s the inductance of the windings, R the resistance of the windings, Ψ_0 the motor constant and p the number of pole pairs. U_{sd} and U_{sq} represent the control action voltages, I_q describes the acting current in the motor and I_d the blind current respectively. ω_m represents the angular velocity of the motor shaft. The current I_q is directly responsible for the torque acting on the motor shaft, whereas I_d has no effect and describes the loss in the motor. Therefore I_d will be controlled to be 0 by the current controller of the motor.

The model of the three-phase electrical system is based on a coordinate transformation from a three-phase AC voltage to a two-dimensional DC voltage representation. This DC representation in d,q - coordinates is based in the rotor coordinate system, eliminating all AC effects. The coordinate transformation is depicted in Figure 1.

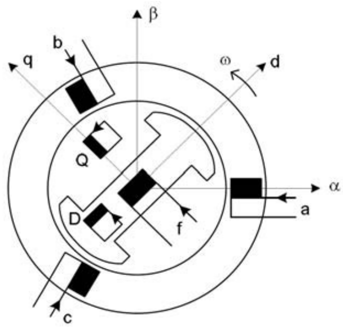

Fig. 1. 3-phase Model by [7]

3.2. Mechanical Model

The model of the connected spindle mechanics looks as follows:

$$\Theta_{tot}\frac{\mathrm{d}\omega_m(t)}{\mathrm{dt}} = \frac{3}{2}p\Psi_0 I_q - \mu_s \mathrm{sign}(\omega_m(t)) - \mu_v\omega_m(t) - F_p\frac{n10^{-3}}{2\pi\gamma} \quad (3)$$

which describes a mechanical architecture as depicted in Figure 2.

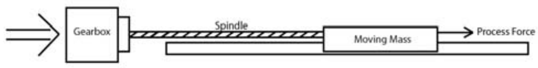

Fig. 2. Mechanical Architecture

The mechanics consist of a gearbox with transmission ratio γ and a spindle with an increment of n mm per revolution. The moving mass, the inertia of the spindle, gearbox and motor are all lumped into one parameter Θ_{tot} which describes the total inertia of the system. The process force, which acts on the linear moving mass is described as F_p. Additionally, a speed dependant friction model is used, with coefficients μ_s and μ_v which consist of the friction of the moving mass on the bearings, the friction of the spindle nut and the gearbox friction. The friction is speed-dependant with a static friction part μ_s and a dynamic friction part μ_v.