MODEL-BASED FAULT DETECTION OF VACUUM CLEANER MOTORS

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Abstract

A semi-physical model aimed for detection of incipient faults in electrical motors is presented. In order to gain high sensitivity to faults a physical model is combined with a black-box model based on Adaptive Network-based Fuzzy Inference System (ANFIS) as a corrective term. The method is applied to vacuum cleaner motors. The architecture and hybrid learning procedure is presented. In the first step, parameters of the physical model are identified by simple least-squares method. Then, the modelling error is compensated by adaptive network learning procedure. This way, the meaning of the physical parameters can be preserved. Diagnostic results show higher sensitivity to faults, which enables reliable fault detection. Consequently, false and missed alarm ratio is reduced as well.

1 Introduction

Competition on the market is forcing the production companies to steadily increase the product quality and reliability. The trends lead to 100% product quality assurance, which leads to reduced service costs.

This paper addresses modelling of vacuum cleaner motors produced by company Domel, which is among greater European manufacturers. The unit consists of a universal motor and an air turbine as load. The production line is highly automated. Priority is given to quality assurance by means of elaborated statistical procedures for quality control of final products. A future modernisation plan includes automatic quality testing of single units at the end of the production line, which would eliminate all defective units.

The prototype system for final quality control of vacuum cleaner motors consists of several functionally different modules [6] (mechano-electrical model, vibration analysis, noise analysis, commutation analysis). In sequel, semi-physical modelling of vacuum cleaner motors for diagnostic purposes is discussed in more detail.

Some model-based solutions for fault detection of electrical motors are known from the literature [1,2,7]. However, they are usually limited to nominal physical models and rely on parameter estimation techniques. But when motors are driven by AC voltage, changes in magnetic field imply non-linear characteristics that are not considered correctly, leading to large modelling error. Consequently, only larger faults can be reliably detected.

A way to increase sensitivity to faults is to use a mathematical model made of two parts, i.e. a physical model and a corrective term that accounts for unmodelled non-linear magnetic characteristic of rotor and stator. The identification of such a hybrid model is based on learning procedure known from adaptive networks. The structure is usually known in advance, while the parameters are determined by optimisation on input-output data of the process [5]. In the given example, the Adaptive-Network-based Fuzzy Inference System (ANFIS) [4] was chosen due to its relatively simple implementation in practice.

The paper is organised as follows. Second chapter describes the ANFIS method with the hybrid learning procedure. It is followed by modelling of the vacuum cleaner motor in the third chapter. Physical model, as well as the principle of modelling error compensation, is given. Diagnostic results are presented in the fourth chapter. Conclusions follow at the end.

2 Adaptive Network-based Fuzzy Inference System - ANFIS

2.1 ANFIS Structure

Let's assume a system with two inputs x and y and one output $z=f$. The system can be described by two fuzzy rules of first-order Sugeno-Takagi type:

- *if* x *is* A_1 *and* y *is* B_1 *then* $f_1=p_1x+q_1y+r_1$
- *if* x *is* A_2 *and* y *is* B_2 *then* $f_2=p_2x+q_2y+r_2$

The same system can be represented as an Adaptive-Network-based Fuzzy Inference System (ANFIS) as shown on Figure 1 [4].

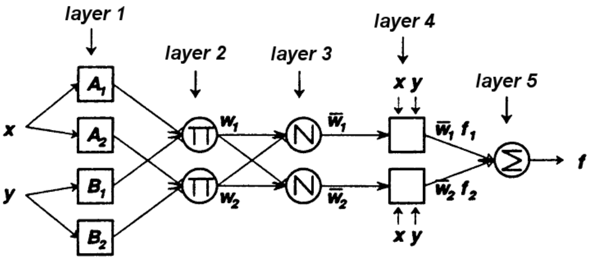


Figure 1: ANFIS example

Adaptive nodes include parameters and are denoted as squares. In the learning procedure, the parameters change accordingly. Fixed nodes are denoted as circles and have no parameters. Their function is to perform the predefined operation. The structure is a 5-layer adaptive feedforward network. The functions of layers and particular nodes are as follows:

Layer 1: Each node i in this layer is adaptive with membership function:

$$O_i^1 = \mu_{A_i}(x) \tag{1}$$

O_i^1 is a degree of membership for variable x to linguistical terms A_i, which are described by their membership functions. Functions $\mu_{A_i}(x)$ are usually defined as Bell functions:

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}, \tag{2}$$

where $\{a_i, b_i, c_i\}$ denote parameters of adaptive nodes and are called *premise parameters*.

Layer 2: Each node i in this layer is a fixed node denoted as Π, which output is the product of all inputs:

$$w_i = \mu_{A_i}(x)\cdot\mu_{B_i}(y) \tag{3}$$

The output w_i represents the weight of the decision rule. In general, minimum operator is also possible.

Layer 3: Each node i in this layer is a fixed node denoted as N, which normalises the weight of the decision rule according to the sum of all weights:

$$\overline{w}_i = \frac{w_i}{\sum w_i} \tag{4}$$

The outputs are normalised weights of decision rules.

Layer 4: Each node i in this layer is adaptive with function:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i), \tag{5}$$

where $\{p_i, q_i, r_i\}$ denote parameters of the adaptive node i and are called *consequent parameters*.

Layer 5: The only node in this layer is a fixed node denoted as Σ, which calculates the output as the sum of all inputs:

$$O_1^5 = f = \sum \overline{w}_i f_i \tag{6}$$

The adaptive network with such structure is functionally equal to the classical representation of the fuzzy inference system [4].

2.2 Hybrid learning procedure

It is obvious from the given structure (eq. 5), that the output of the system is a linear combination of consequent parameters:

$$\begin{aligned} f &= (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 \\ &\quad + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \end{aligned} \tag{7}$$

These parameters can easily be identified by simple *least-squares* method [4]. In matrix form, the equation can be written as:

$$AX = B \tag{8}$$

where B stands for input vector, A denotes the matrix of linear input equations, and X represents an unknown vector of consequent parameters. The estimates are then given by:

$$\hat{X} = (A^T A)^{-1} A^T B\,. \tag{9}$$

Parameters of non-linear conditional part are identified by gradient method [4]. If α denotes a premise parameter in layer 1 of the network, the change can be defined as:

$$\Delta\alpha = -\eta\frac{\partial E}{\partial \alpha} \tag{10}$$

where E stands for output error and η for learning rate, which can be further expressed as:

$$\eta = \frac{k}{\sqrt{\sum_{\alpha}\left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{11}$$

where k is the step size (length) of each gradient transition in the parameter space and affects the speed of convergence. Small k closely approximates the gradient path, but leads to slow convergence. On the other hand, large k leads to fast convergence, but causes oscillations around the optimum. The problem is solved by simple heuristic rules [4].

The overall learning procedure is as follows [4]. First, at each iteration step, consequent parameters are identified by least-squares method based on given input-output data. Then, gradient method is used for identification of premise parameters in non-linear part based on current output error (back-propagation).

3 Vacuum cleaner motor

3.1 Description

Vacuum cleaner motor is a single-phase commutation motor whose construction and working principle are the same as in DC motors. It is also referred to as universal motor because it can run under AC and DC voltage supply. Owing to the fact that stator and rotor windings are serially connected and load current flows through the excitation windings, the largest motor torque is achieved. This electric motor has also a big start-up torque. The main weak point is commutation, i.e. problems of sparking and brush wear, which seriously affect the device lifetime.

Main parts of the vacuum cleaner motor are shown in Figure 2. Fan impeller with nine shovels mounted on motor's shaft generates airflow through the hole in the cover. The diffuser directs then the airflow through the orifice between stator in order to cool the motor. The nominal rotational speed of those motors is 550 Hz.

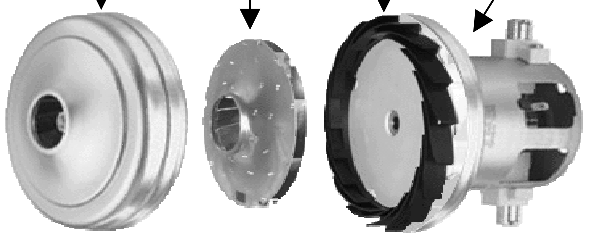


Figure 2: Components of the vacuum cleaner motor

3.2 Physical model

Physical laws governing the motor are given by the following equations:

electrical part:

$$u(t) = i(t)(R_v + R_a) + K \cdot i(t) \cdot \omega(t) + (L_v + L_a)\frac{di(t)}{dt}, \tag{12}$$

mechanical part:

$$J\frac{d\omega(t)}{dt} = K \cdot i^2(t) - M_0 - M_1\omega(t) - M_2\omega^2(t),\ \omega > 0 \tag{13}$$

The meaning of parameters is as follows: R_v and R_a stand for stator and rotor resistances, L_v and L_a are stator and rotor inductances, K represents magnetic flux coefficient, and J is inertia constant. Air turbine as load is characterised by dry friction M_0, viscous friction M_1, and turbulent friction M_2 coefficients.

Supply voltage *u(t)* represents process input. The two states, current *i(t)* and rotational speed *ω(t),* are measurable and represent system outputs. The electrical wiring is given in Figure 3. As stator and rotor windings are serially connected, only joint resistance R and inductance L can be identified.

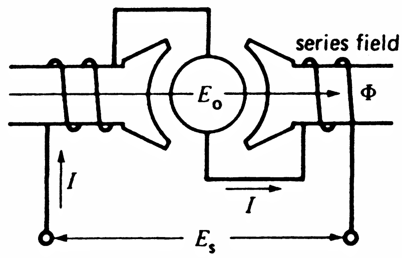


Figure 3: Motor wiring

The motor is driven by AC voltage with a profile suitable for stimulating all the dynamical modes of the system. Then, all parameters are identified by least-squares method in continuous time domain. The measurements are sampled at 10 kHz and filtered by low-pass Butterworth filter with cut-off frequency of 250 Hz. The comparison between physical model and actual measurements is given in Figure 4. Here, RMS value of current *i(t)* and rotational speed *ω(t)* are shown.

Modelling error is defined as a difference between measured and predicted output of the system:

$$e_{electrical} = i(t) - i_m(t) \quad \text{and}$$

$$e_{mechanical} = \omega(t) - \omega_m(t) \tag{14}$$

The results show error to signal ratio of roughly 20% for electrical part and 5% for mechanical part. While the accuracy of the mechanical model is acceptable, the obtained electrical model is unacceptable for diagnostic purposes [3]. It is assumed that such a big error is caused by unmodelled non-linear magnetic characteristic (i.e. hysteresis, magnetic saturation) as the motor is driven by AC voltage. For simplicity, only electrical model will be elaborated.

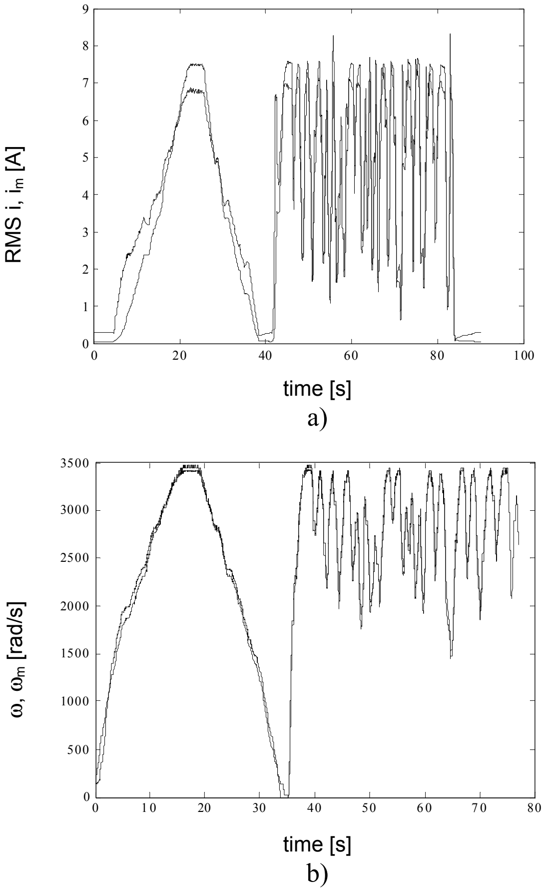


Figure 4: Physical model validation
a) electrical part, b) mechanical part

3.3 Compensation of modelling error

To achieve higher fault sensitivity, the compensation of modelling error can be employed [3]. This is done by combining the physical model with a black-box model based on ANFIS introduced in the previous chapter. By keeping the nominal model description, physical parameters are preserved that are necessary for fault isolation [3]. The main problem of fault detection is caused by non-structured modelling error with unknown parameters and unfamiliar theoretical background. In this case, a *parallel* hybrid model seems suitable for on-line compensation in real time [8].

The principle of compensation of the modelling error is shown in Figure 5. The necessary inputs to the adaptive network are process input, model output, and modelling error (residual). During learning stage, the actual residual is used, while during on-line usage, the predicted error is utilised. Otherwise, error caused by faulty behaviour could also be compensated, which would make some faults undetectable.

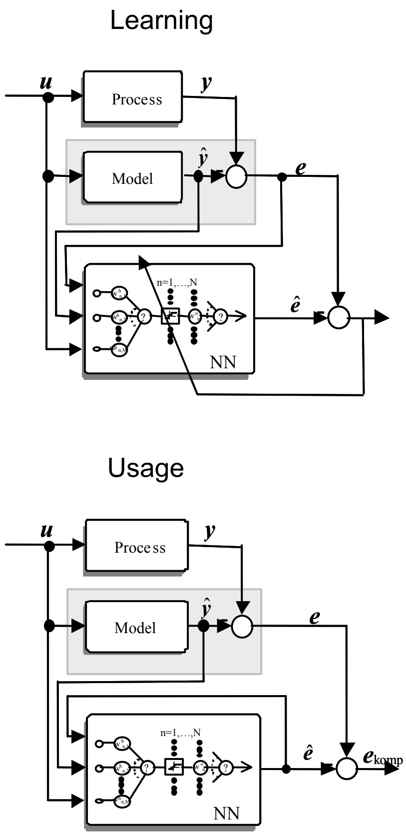


Figure 5: Principle of modelling error compensation

3.4 Hybrid model

In the given case, supply voltage $u(t)$, current $i(t)$ and rotational speed $\omega(t)$ were chosen as inputs to the adaptive network, while modelling error of the current was chosen as output. Preliminarily, several delayed inputs were also considered due to the expected nonlinearity with memory (i.e. hysteresis). However, acceptable model accuracy was achieved by simple static relation.

Three membership functions were chosen for each input, resulting in the following ANFIS model structure:

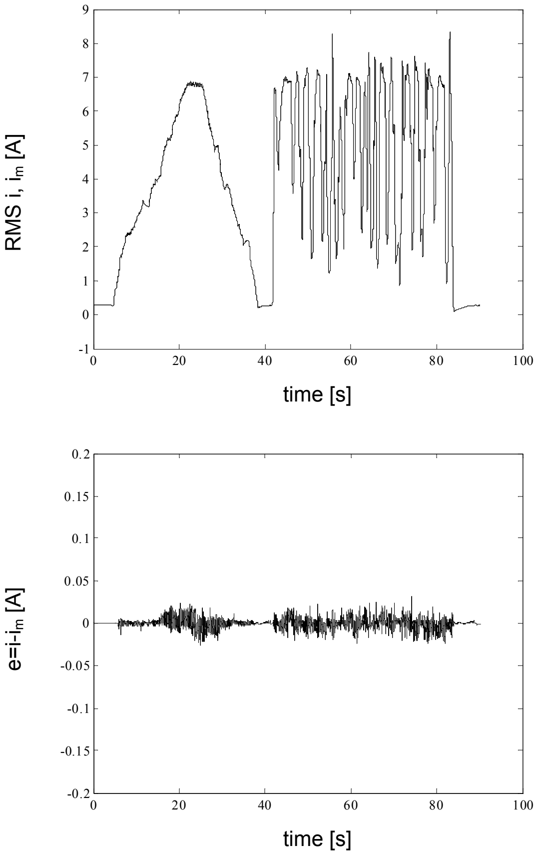
- number of nodes: 91
- number of consequent parameters: 108
- number of premise parameters: 27
- number of fuzzy decision rules: 27

The resulting hybrid model is identified in two steps. Firstly, parameters of the physical model are estimated by simple least-squares method. Then, a learning procedure for adaptive networks (Section 2.2) is applied in order to compensate errors resulting from nominal model (eq. 12).

4 Diagnostic results

4.1 Validation

Validation was performed on a series of 10 motors. Figure 6 shows time plots of electrical part for the fault-free motor with its predicted hybrid model output and the resulting residual *e*.



e_{RMS}=0.0054

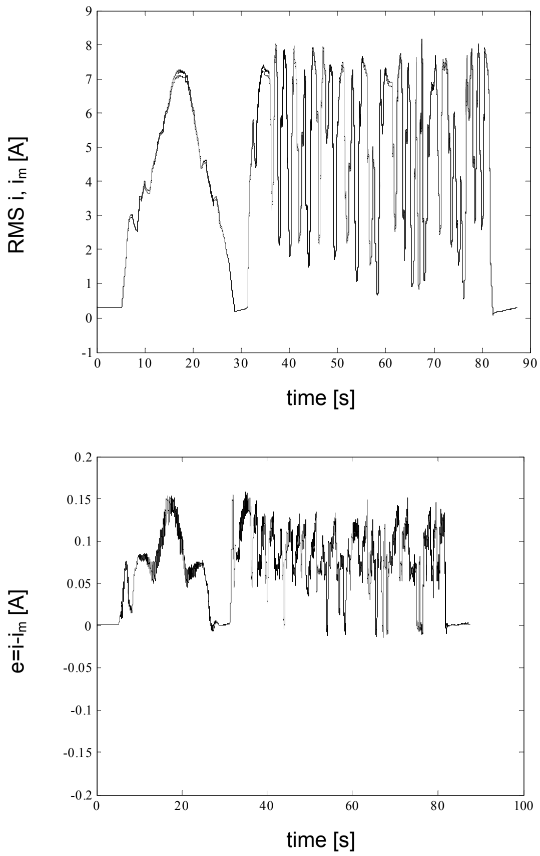
Figure 6: Validation of the hybrid model

Results show that error to signal ratio reduces to less than 1% roughly. It is important to note that model parameters are identified once per motor type and that the model prediction is then used in fault detection.

4.2 Fault detection

The same hybrid model is further applied to the motor with a fault in electrical part (sparking of the brushes). Only abrupt faults are considered, as the purpose of the diagnostic system is to detect inherent faults at the end of the production line. The output is shown in Figure 7.

Results show that the model discrepancy increases more then 10-times and can therefore be used as a reliable feature for fault detection. Other faults were also tested (rotor unbalance, bad bearings) and similar results were obtained.



e_{RMS}=0.0801

Figure 7: Hybrid model applied to faulty motor

5 Conclusions

Model-based fault detection of vacuum cleaner motors is presented. Fault detection relies on energy balance conservation laws. Discrepancy between measured and predicted values reflect the presence of a fault. Any modelling error directly affects sensitivity to faults.

To account for unmodelled non-linear characteristics, the principle of compensating the modelling error by ANFIS is chosen. Diagnostic results on real devices show significant reduction of the modelling error, which enables higher fault sensitivity. Consequently, false and missed alarm ratio is reduced as well.

However, good excitation during the learning phase at each change of the motor type is required, which stimulates all the dynamical modes of the system. Also, the isolation ability is limited to either electrical or mechanical part. To some extend, further differentiation is then possible by employing classical parameter estimation techniques.

Acknowledgements

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