HYBRID MODELLING OF ELECTRICAL MOTORS FOR DIAGNOSTIC PURPOSES

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Abstract: The paper presents hybrid modelling of electrical motors. To improve diagnostic performance, the analytical model is combined with Adaptive-Network-based Fuzzy Inference System (ANFIS) to compensate the modelling error. The architecture and hybrid learning procedure is presented. The method is applied to vacuum cleaner motors. The unit consists of a universal motor with stator and rotor coils in series and air turbine as load. Necessary measurements are supply voltage, current and speed of rotation. In the first step, parameters of analytical model are identified by simple least-square method. Then, the modelling error is compensated by hybrid learning procedure. This way, the meaning of the physical parameters can be preserved. Diagnostic results show higher sensitivity of faults without affecting detectability. False alarms are minimised which improves the reliability of the whole diagnostic system.

Keywords: fault detection, modelling, universal motor, neural networks

1. INTRODUCTION

Competition on the market is forcing the production companies to steadily increase the product quality and reliability. The trends lead to 100% quality assurance of components, which minimises the costs of servicing the final products.

This paper addresses modelling of vacuum cleaner motors produced by company Domel, which is a renowned European producer. The unit consists of a universal motor and 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 (Tinta *et al.*, 2002) (mechano-electrical model, vibration analysis, noise analysis, commutation analysis). In sequel, modelling of electrical motors for diagnostic purposes is discussed. Due to unmodelled physical processes (hysteresis, core saturation), the analytical model is combined with a black-box model for compensating the modelling error, which improves the sensitivity of a diagnostic system to faults.

The identification of such hybrid model is based on learning stage known from artificial neural nets. The structure is usually known in advance, while the parameters are determined by optimisation on input-output data of the process (Takagi and Sugeno, 1985). In the given example, the Adaptive-Network-based Fuzzy Inference System (ANFIS) (Shing and Jang, 1993) was used 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 electrical motor in the third chapter. Analytical model, as well as the principle of modelling error compensation, are 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

Lets have 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.

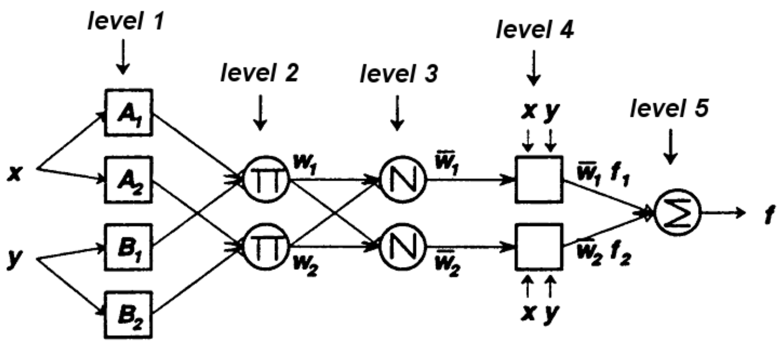


Figure 1: ANFIS example

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 directed neural net includes 5 levels. The structure and functions of particular levels are as follows:

Level 1: Each node *i* on this level 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. Membership 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*.

Level 2: Each node i on this level 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.

Level 3: Each node i on this level 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.

Level 4: Each node i on this level 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*.

Level 5: The only node on this level 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 neural net with such structure is functionally equal to the classical representation of the fuzzy inference system (Shing and Jang, 1993).

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:

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

These parameters can easily be identified by simple *least-squares* method (Shing and Jang, 1993). Parameter estimates are given by:

$$\hat{X} = (A^T A)^{-1} A^T B \tag{8}$$

where B stands for input vector and A denotes the matrix of linear input equations.

Parameters of nonlinear conditional part (level 1) are identified by gradient method (Shing and Jang, 1993). The parameter change can be defined as:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{9}$$

where E stands for output error and η for speed of learning.

Learning procedure is performed in two steps (Shing and Jang, 1993). 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 nonlinear part based on current output error (back-propagation).

3. VACUUM CLEANER MOTOR

3.1 Analytical model

The process under investigation is a vacuum cleaner motor of type 462.3.451 produced by company Domel (Figure 2).

Figure 2: Vacuum cleaner motor

Supply voltage *u(t)* represents process input and air turbine as load. 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.

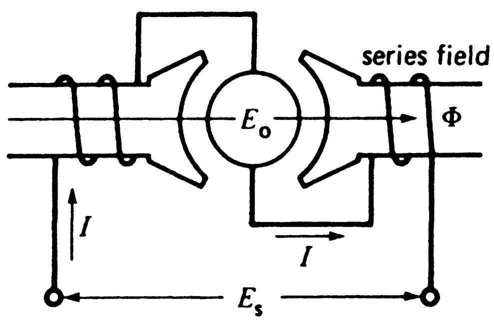


Figure 3: Motor wiring

The presumed model structure based on physical laws is given by the following equations:

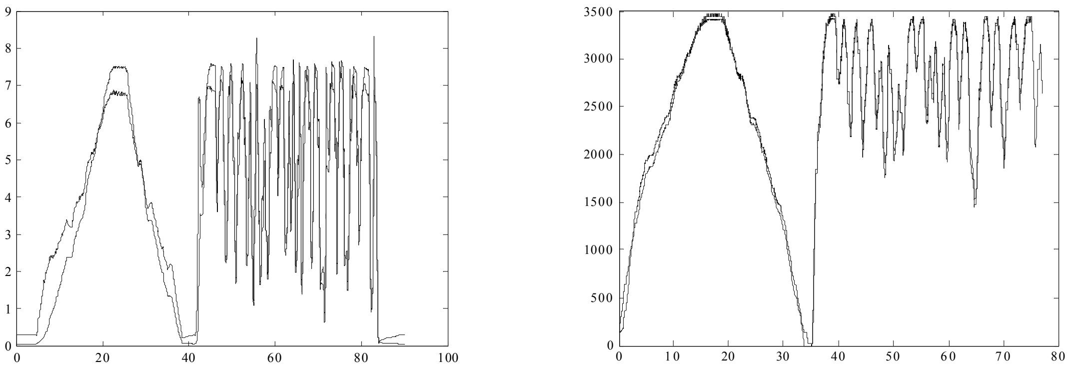
electrical part:

$$u(t) = i(t)(R_v + R_a) + K \cdot i(t) \cdot \omega(t) + (L_v + L_a)\frac{di(t)}{dt}, \tag{10}$$

mechanical part:

$$J\frac{d\omega(t)}{dt} = K \cdot i^2(t) - M_0 - M_1\omega(t) - M_2\omega^2(t)\text{, }\omega>0 \tag{11}$$

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 analytical model and actual measurements is shown in Figure 4.



a) b)

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

The results show 20% modelling error in electrical part and 5% modelling error in mechanical part. This is caused by unmodelled physical processes (i.e. hysteresis, core saturation). Unfortunately, the accuracy of the electrical model is unacceptable for diagnostic purposes (Rakar, 2000).

3.2 Compensation of modelling error

To achieve higher fault sensitivity, the compensation of the modelling error can be employed (Rakar, 2000). This is done by combining the analytical model with a black-box model based on ANFIS introduced in the previous chapter. By keeping the analytical model description, physical parameters are preserved, which enables fault isolation (Rakar, 2000).

The principle of compensation of the modelling error is shown in Figure 5

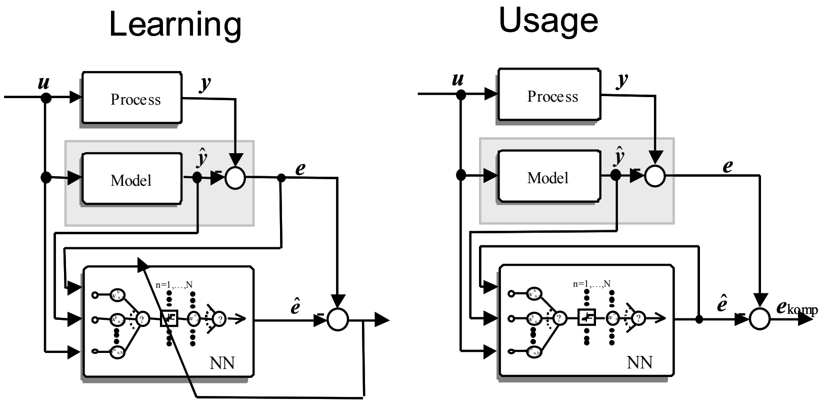


Figure 5: Principle of modelling error compensation

3.3 Hybrid modelling

The system is modelled in MATLAB environment. Fuzzy logic toolbox already includes ANFIS function for building fuzzy models. The function supports models with multiple inputs and single output. In the given case, supply voltage *u(t)*, current *i(t)* and speed *ω(t)* are chosen as inputs to the neural net, while modelling error of the current is chosen as output.

Then, three membership functions were chosen for each input. No a priori system knowledge was available, thus the number was chosen empirically to achieve acceptable model accuracy.

Initial membership function parameters were chosen to obtain uniform distribution in the whole region of input variables (function GENFIS1 in Matlab).

The final ANFIS model has the following characteristics:

- number of nodes: 81
- number of linear parameters: 81
- number of nonlinear parameters: 18
- number of fuzzy decision rules: 27

The final structure of the ANFIS model is given in Figure 6

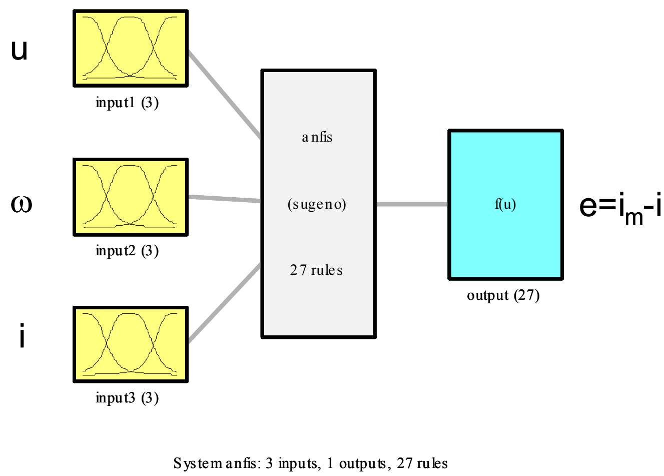
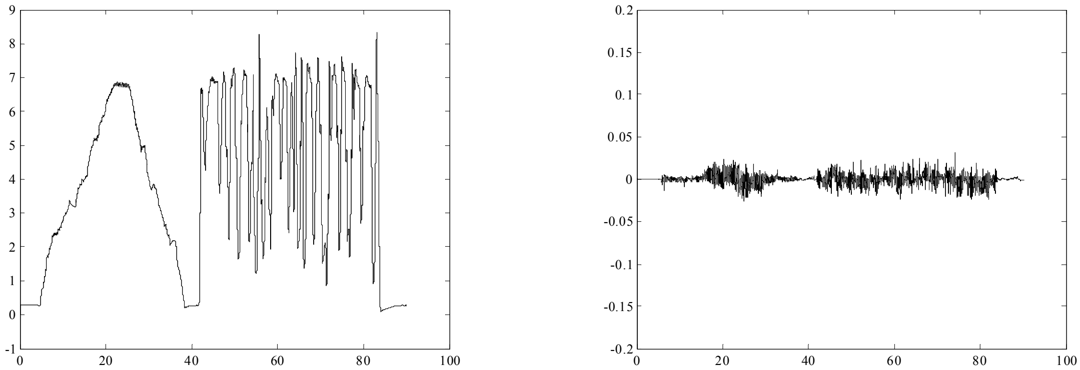


Figure 6: Structure of ANFIS model

4. DIAGNOSTIC RESULTS

4.1 Validation

Validation is performed on a different set of measurements. Output estimation based on given inputs is obtained by Matlab function EVALFIS. Figure 7 shows time plots of electrical part for the same good motor and its hybrid model output.



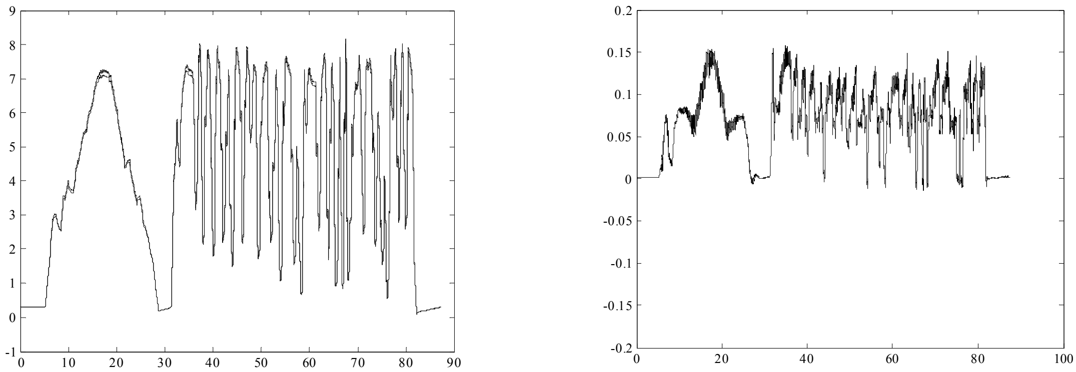
$e_{RMS}=0.0054$

Figure 7: Validation of the hybrid model

Results show significant reduction of the modelling error, although a simple static model was used in compensation. Hovever, this does not affect fault detectability (Rakar, 2000).

4.2 Fault detection

The same hybrid model is then applied to the vacuum cleaner motor with a fault in electrical part (sparking of the brushes). The output is shown in Figure 8.



$e_{RMS}=0.0801$

Figure 8: Hybrid model applied to faulty motor

Results show that the model discrepancy increases more then 10-times and can therefore be used as a reliable feature for fault detection.

5. CONCLUSIONS

The paper shows a principle of compensating the modelling error for diagnosing electrical motors based on ANFIS models.

By employing the proposed hybrid model, the unmodelled dynamics (histeresis, core saturation) is compensated, which enables higher sensitivity. This way, every unconsistency in energy balance can be detected. However, good excitation during the learning phase at each change of the motor type is necessary. Also, suitable choice of initial membership functions and learning parameters are necessary.

Diagnostic results on real examples show significant reduction of the modelling error without affecting fault detectability. Higher sensitivity is achieved and false alarms are minimised which improves the reliability of the whole system for quality control of vacuum cleaner motors.

6. ACKNOWLEDGEMENTS

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