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Modeliranje elektromotorjev za potrebe zaznavanja napak

Modelling for Fault Detection of Electric Motors

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Prispevek podaja semi-fizikalni model za potrebe zaznavanja zgodnjih napak elektromotorjev. Da bi dosegli veliko občutljivost na napake, fizikalni model kombiniramo z modelom, ki temelji na sistemu mehkega sklepanja na podlagi adaptivnih nevronskih mrež (MSSANM - ANFIS). Metodo uporabimo na realnem primeru elektromotorja sesalne enote. Predstavljena sta zgradba modela in hibridni postopek učenja. V prvem koraku najprej identificiramo parametre fizikalnega modela z osnovno metodo najmanjših kvadratov. Nato kompenziramo odstopanje modela z učenjem adaptivne nevronske mreže. Tako lahko ohranimo pomen fizikalnih parametrov. V nadaljevanju so prikazani rezultati zaznavanja električnih napak motorja (iskrenje ščetk, spremembe v električnih parametrih ipd.), kjer je odstopanje fizikalnega modela najbolj izrazito. Diagnostični rezultati kažejo povečano občutljivost na napake, kar omogoča večjo zanesljivost zaznavanja napak. Posledično se zmanjša tudi število lažnih alarmov in spregledanih napak.

(Ključne besede: zaznavanje napak, modeliranje, identifikacija, elektromotorji univerzalni, mreže adaptivne)

A semi-physical model aimed at detection of incipient faults in electric motors is presented. In order to gain high sensitivity to faults a physical model is combined with a black-box model based on an 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, the parameters of the physical model are identified by a simple least-squares method. Then, the modelling error is compensated using an adaptive-network learning procedure. In this way, the meaning of the physical parameters can be preserved. Next, the detection of the electrical faults of the motor – sparking of the brushes, changes in electrical parameters, etc. – are presented, where there is the most significant physical modelling error. The diagnostic results show a higher sensitivity to faults, which enables reliable fault detection. Consequently, the false and missed alarm ratio is reduced as well.

(Keywords: fault detection, modelling, identifications, universal motors, adaptive networks)

0 UVOD

Konkurenčne razmere na trgu silijo proizvajalce v stalno dvigovanje kakovosti in zanesljivosti izdelkov proizvodnje. Težnje gredo praktično v smeri zagotavljanja 100-odstotne brezhibnosti sestavnih delov, s čimer se zmanjšajo stroški servisiranja končnih izdelkov.

V tem prispevku obravnavamo elektromotor sesalne enote proizvajalca Domel d.d., ki je ugleden evropski izdelovalec. Sesalno enoto sestavlja sklop univerzalnega motorja in zračne turbine. Postopek izdelave je razmeroma visoko avtomatiziran, pri čemer je veliko poudarka na zagotavljanju kakovosti s posebnimi postopki statistične kontrole izdelkov. Želja je, da bi bila vsaka sesalna enota po končani montaži podvržena temeljitemu avtomatskemu testu kakovosti, s čimer bi izločili vse enote s pomanjkljivostmi oz. napakami.

0 INTRODUCTION

Competition on the market is forcing companies to steadily increase product quality and reliability. This trend leads to 100% product quality assurance, which means to reduced service costs.

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

Prototip sistema za končno kontrolo sesalnih enot sestavlja več funkcionalno ločenih modulov [7] (mehansko-električni model, analiza vibracij, analiza hrupa, analiza kakovosti komutacije). V nadaljevanju se omejimo na modeliranje elektromotorjev sesalnih enot za potrebe zaznavanja napak.

V literaturi najdemo kar nekaj pristopov k modeliranju za zaznavanje napak elektromotorjev ([1], [2] in [8]). Vendar so le-ti navadno omejeni na uporabo nominalnih fizikalnih modelov in različnih tehnik identifikacije parametrov. Ko elektromotorje napajamo z izmenično napetostjo, se pojavijo spremembe v magnetnem polju, ki vodijo do nelinearnosti, ki jih je težko pravilno opisati. Posledica tega je veliko odstopanje modela, kar pomeni, da lahko zaznamo le večje napake v delovanju.

Občutljivost na napake lahko povečamo s hibridnim matematičnim modelom, ki ga sestavljata dva dela: fizikalni model in korekcijski člen, ki predstavlja nemodelirano magnetno karakteristiko rotorja in statorja. Identifikacija takega hibridnega modela je pravzaprav postopek učenja, ki ga poznamo pri adaptivnih mrežah. Struktura modela je navadno določena vnaprej, z optimizacijo pa iščemo parametre na podlagi vhodno-izhodnih meritev postopka [6]. V danem primeru smo izbrali sistem mehkega sklepanja na podlagi adaptivnih nevronskih mrež (MSSANM) [5], ki ga je razmeroma preprosto realizirati tudi v praksi.

Prispevek je organiziran takole. Prvo poglavje podaja kratek opis metode MSSANM s hibridnim postopkom učenja. Drugo poglavje je namenjeno modeliranju elektromotorja sesalne enote. Podan je fizikalni model in princip kompenzacije odstopanja modela. Diagnostični rezultati so prikazani v tretjem poglavju. Sledijo še glavni sklepi.

The prototype system for the final quality control of vacuum-cleaner motors consists of several functionally different modules [7]: mechano-electrical model, vibration analysis, noise analysis, and commutation analysis. Next, semi-physical modelling of vacuum-cleaner motors for diagnostic purposes is discussed in more detail.

Some model-based solutions for the fault detection of electric motors are known from the literature ([1], [2] and [8]). 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 the magnetic field imply non-linear characteristics that are not considered correctly, leading to a large modelling error. Consequently, only larger faults can be reliably detected.

A way to increase the 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 the unmodelled non-linear magnetic characteristics of the rotor and the stator. The identification of such a hybrid model is based on a learning procedure known from adaptive networks. The structure is usually known in advance, while the parameters are determined by optimisation on the input-output data of the process [6]. In the given example, the Adaptive-Network-based Fuzzy Inference System (ANFIS) [5] was chosen due to its relatively simple implementation in practice.

The paper is organised as follows. The first section describes the ANFIS method with the hybrid learning procedure. It is followed by the modelling of the vacuum-cleaner motor in the second section. The physical model, as well as the principle of modelling-error compensation, is given. The diagnostic results are presented in the third section. The conclusions follow at the end.

1 SISTEM MEHKEGA SKLEPANJA NA PODLAGI ADAPTIVNIH NEVRONSKIH MREŽ - MSSANM

1 THE ADAPTIVE NETWORK-BASED FUZZY INFERENCE SYSTEM - ANFIS

1.1 Zgradba MSSANM

Vzemimo sistem z dvema vhodoma x in y ter enim izhodom $z=f$. Opišemo ga lahko z dvema mehkima praviloma tipa Sugeno-Takagi prvega reda:

1.1 ANFIS Structure

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

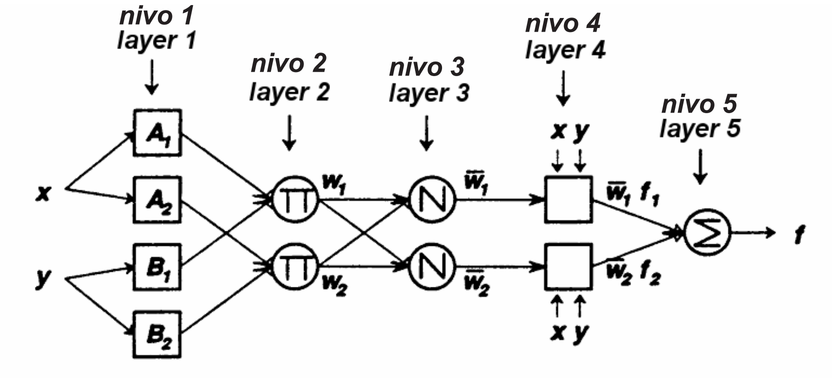
$$\begin{aligned} &if\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ f_1=p_1x+q_1y+r_1 \\ &if\ x\ is\ A_2\ and\ y\ is\ B_2\ then\ f_2=p_2x+q_2y+r_2 \end{aligned} \quad (1)$$

Isti sistem lahko predstavimo v obliki mehkega sklepanja na podlagi adaptivnih nevronskih mrež - MSSANM [5], kakor prikazuje slika 1.

Adaptivna vozlišča vsebujejo parametre in so označena s pravokotniki. V postopku učenja se vrednosti teh parametrov ustrezno spreminjajo. Fiksna vozlišča, ki so označena s krogi, izvajajo le

The same system can be represented as an Adaptive-Network-based Fuzzy Inference System (ANFIS), as shown in Figure 1 [5].

Adaptive nodes include parameters and are denoted as squares. In the learning procedure, the parameters change accordingly. The fixed nodes are denoted as circles and have no parameters. Their



Sl. 1. *Primer MSSANM*
Fig. 1. *ANFIS example*

izbrano operacijo in ne vsebujejo parametrov. Adaptivna nevronska mreža je 5-nivojska usmerjenega tipa. Funkcije nivojev in posameznih vozlišč so:

Nivo 1: Vsako vozlišče *i* na tem nivoju je adaptivno s funkcijo:

function is to perform the predefined operation. The structure is a 5-layer adaptive feed-forward network. The functions of the layers and the particular nodes are as follows:

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

$$O_i^1 = \mu_{A_i}(x) \tag{2}$$

O_i^1 je stopnja pripadnosti spremenljivke *x* jezikovnim vrednostnim A_i, ki jih opisujejo njihove pripadnostne funkcije. Za pripadnostne funkcije $\mu_{A_i}(x)$ po navadi izberemo funkcijo zvonaste oblike:

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-shaped functions:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3}$$

kjer so $\{a_i, b_i, c_i\}$ parametri adaptivnega vozlišča *i* in jih imenujemo *pogojni parametri*.

Nivo 2: Vsako vozlišče *i* na tem nivoju, označeno s Π, je fiksno vozlišče, ki pomnoži vhode O_i^1 in njihov zmnožek poda na izhodu:

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, the output of which is the product of all the inputs O_i^1:

$$w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \tag{4}$$

Izhod w_i je torej *utež odločitvenega pravila*. V splošnem lahko namesto zmnožka uporabimo tudi opravilo minimuma.

Nivo 3: Vsako vozlišče *i* na tem nivoju je fiksno vozlišče, označeno z N. Utež odločitvenega pravila w_i normiramo glede na vsoto vseh uteži:

The output w_i represents the *weight of the decision rule*. In general, the minimum operator instead of the product 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 w_i according to the sum of all the weights:

$$\overline{w}_i = \frac{w_i}{\sum w_i} \tag{5}$$

Izhodi $\overline{w}_i$ so torej normirane uteži odločitvenih pravil.

Nivo 4: Vsako vozlišče *i* na tem novoju je adaptivno s funkcijo:

The outputs $\overline{w}_i$ are normalised weights of the decision rules.

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

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{6}$$

kjer so parametri $\{p_i, q_i, r_i\}$ funkcije f_i adaptivni parametri vozlišča i in jih imenujemo *posledični parametri.*

Nivo 5: Edino vozlišče na tem noviju je fiksno vozlišče, označeno s Σ, ki izračuna celotni izhod f kot vsoto vseh vhodov O_i^4 v vozlišče:

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 f as the sum of all the inputs O_i^4:

$$O_1^5 = f = \sum \overline{w}_i f_i \tag{7}$$

Adaptivna nevronska mreža s tako strukturo je funkcijsko enakovredna klasični predstavitvi sistema mehkega sklepanja [5].

The adaptive network with such a structure is functionally equal to the classical representation of the fuzzy inference system [5].

1.2 Hibridni postopek učenja

1.2 Hybrid learning procedure

Iz predlagane strukture (en. 6) je razvidno, da je izhod sistema f linearna kombinacija posledičnih parametrov $\{p_i, q_i, r_i\}$:

It is obvious from the given structure (Eq. 6), that the output of the system f is a linear combination of the consequent parameters $\{p_i, q_i, r_i\}$:

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \tag{8}$$

Te parametre lahko torej preprosto določimo z metodo najmanjših kvadratov (MNK - LSE) [5]. Enačbo lahko v matrični obliki zapišemo kot:

These parameters can easily be identified by a simple least-squares method [5]. In matrix form, the equation can be written as:

$$AX = B \tag{9}$$

kjer je B vektor izhodov, A matrika linearnih vhodnih enačb in X vektor neznanih posledičnih parametrov.
Vektor ocene parametrov dobimo kot:

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

$$\hat{X} = (A^T A)^{-1} A^T B \tag{10}$$

Parametre v nelinearnem pogojnem delu določimo z gradientno metodo [5]. Če α predstavlja pogojni parameter nivoja 1 adaptivne mreže, lahko spremembo izrazimo kot:

The parameters of non-linear conditional part are identified by the gradient method [5]. If α represents a premise parameter in layer 1 of the network, the change is denoted as:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{11}$$

kjer je E izhodno odstopanje in η hitrost učenja, ki jo izrazimo kot:

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

$$\eta = \frac{k}{\sqrt{\sum_\alpha \left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{12}$$

kjer je k velikost koraka (dolžina) posameznega gradientnega pomika v prostoru parametrov in vpliva na hitrost konvergence. Mala vrednost k natančno opiše gradientno pot, vendar vodi k počasni konvergenci. Po drugi strani pa z veliko vrednostjo k dosežemo hitro konvergenco, vendar vodi k oscilacijam v okolici optimuma. Problem lahko rešimo s preprostimi hevrističnimi pravili [5].

Celoten postopek učenja poteka v dveh korakih [5]. V vsaki iteraciji najprej na podlagi vhodno-izhodnih podatkov z metodo najmanjših kvadratov določimo posledične parametre. Nato z gradientno

where k is the step size (length) of each gradient transition in the parameter space, and affects the speed of convergence. A small value of k closely approximates the gradient path, but leads to slow convergence. On the other hand, a large value of k leads to fast convergence, but causes oscillations around the optimum. The problem can be solved by simple heuristic rules [5].

The overall learning procedure is as follows [5]. First, at each iteration step, the consequent parameters are identified by a least-squares method based on given input-output data. Then, the gradient metodo na podlagi izhodnega odstopanja določimo še pogojne parametre, ki predstavljajo nelinearni del (vzvratno širjenje).

method is used to identify the premise parameters in the non-linear part based on the current output error (back-propagation).

2 ELEKTROMOTOR SESALNE ENOTE

2 THE VACUUM-CLEANER MOTOR

2.1 Opis

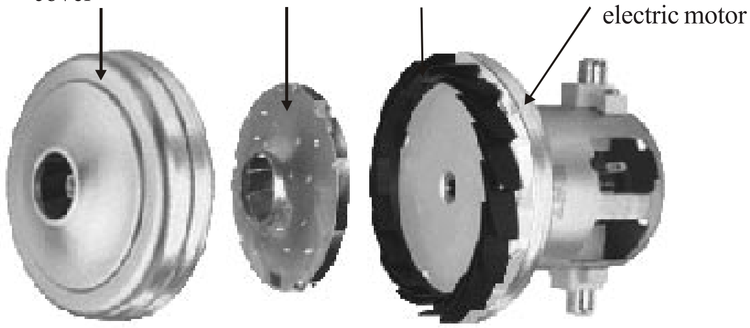
2.1 Description

Elektromotor sesalne enote je enofazni komutacijski motor, ki je po konstrukciji in principu delovanja enak enosmernemu motorju. Znan je tudi po imenu univerzalni motor, ker ga lahko napajamo z izmenično ali enosmerno napetostjo. Ker sta navitji statorja in rotorja zaporedno vezani, tako da teče isti tok skozi obe navitji, dosežemo največji možni mehanski vrtilni moment. Tak elektromotor ima tudi velik startni vrtilni moment. Glavno slabost predstavlja komutacija, ki je povezana z obrabo ščetk, kar močno vpliva na življenjsko dobo naprave.

Glavne sestavne dele sesalne enote prikazuje slika 2. Turbinsko kolo, pritrjeno na osi motorja, z devetimi lopaticami ustvarja zračni tok skozi odprtino na pokrovu zračne turbine. Vloga difuzorja je usmeriti zračni tok skozi režo med statorjem in rotorjem za potrebe hlajenja motorja. Nazivna vrtilna frekvenca obravnavanih motorjev je 550 s^{-1}.

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

The main parts of the vacuum-cleaner motor are shown in Figure 2. The fan impeller with nine shovels mounted on the motor's shaft generates the airflow through the hole in the cover. The diffuser then directs the airflow through the orifice between the stator in order to cool the motor. The nominal rotational speed of such motors is 550 s^{-1}.



Sl. 2. *Sestavni deli sesalne enote*
Fig. 2. *Components of the vacuum-cleaner motor*

2.2 Fizikalni model

2.2 Physical model

Strukturo analitičnega modela na podlagi fizikalnih zakonitosti podajajo naslednje enačbe:
električni del:

The physical laws governing the motor are given by the following equations:
electrical part:

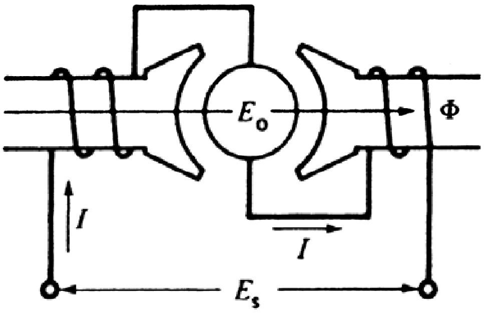
$$u(t) = i(t)(R_v + R_a) + K \cdot i(t) \cdot \omega(t) + (L_v + L_a)\frac{di(t)}{dt} \qquad (13),$$

mehanski del: *mechanical part:*

$$J\frac{d\omega(t)}{dt} = K \cdot i^2(t) - \mu_0 - \mu_1\omega(t) - \mu_2\omega^2(t),\ \omega>0 \qquad (14).$$

Pomen parametrov je naslednji: R_v in R_a predstavljata upornosti navitij statorja in rotorja, L_v in L_a sta induktivnosti statorja in rotorja, K pomeni

The meaning of the parameters is as follows: R_v and R_a stand for the stator and rotor resistances, L_v and L_a are the stator and rotor inductances, K



Sl. 3. *Vezava motorja*
Fig. 3. *Motor wiring*

koeficient magnetnega fluksa ter J konstanto vztrajnosti. Zračno turbino kot breme opišemo s koeficienti suhega μ_0, viskoznega μ_1 in turbulentnega μ_2 trenja.

Vhod v sistem predstavlja napajalna napetost $u(t)$. Dvoje stanj: tok $i(t)$ in vrtilna frekvenca $\omega(t)$ sta merljiva in predstavljata izhoda sistema. Vezavo motorja prikazuje slika 3. Ker sta navitji statorja in rotorja vezani zaporedno, lahko identificiramo le skupno upornost R in induktivnost L navitja.

Motor napajamo z izmenično napetostjo po hitrostnem profilu, ki vzbudi celotno dinamično območje sistema. Nato vse parametre identificiramo z metodo najmanjših kvadratov v zveznem časovnem prostoru. Meritve zajememo s frekvenco vzorčenja 10 kHz, podatke pa nato še filtriramo z nizkoprepustnim Butterworth-ovim filtrom z mejno frekvenco 250 Hz. Ujemanje dobljenega fizikalnega modela z dejanskim motorjem prikazuje slika 4. Prikazana je efektivna vrednost toka $i(t)$ in vrtilna frekvenca $\omega(t)$.

Odstopanje modela definiramo kot razliko med ocenjeno in izmerjeno vrednostjo izhoda sistema:

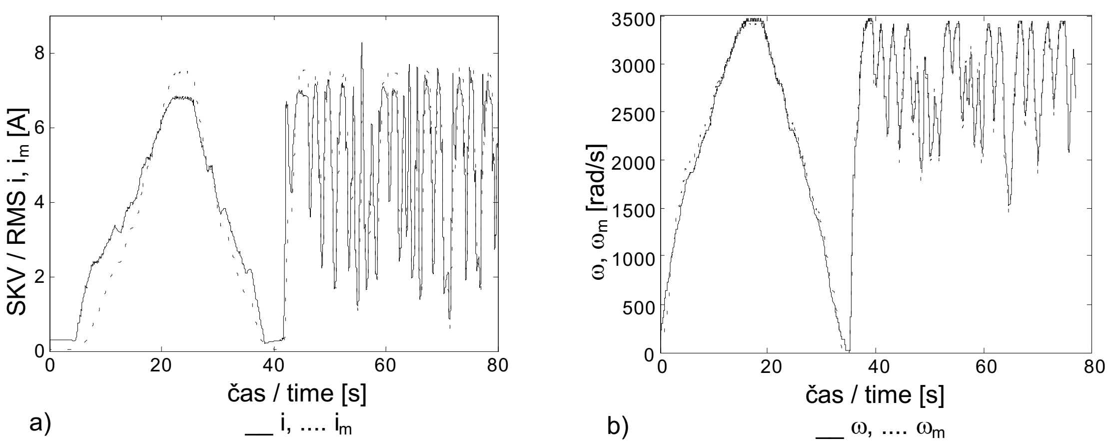
represents the magnetic-flux coefficient, and J is the inertia constant. The air turbine as a load is characterised by the dry friction μ_0, the viscous friction μ_1, and the turbulent friction μ_2 coefficients.

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

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

The modelling error is defined as the difference between the estimated and the measured output of the system:

$$e_{electrical} = i_m(t) - i(t) \quad \text{in / and} \quad e_{mechanical} = \omega_m(t) - \omega(t) \tag{15}$$



Sl 4. *Ujemanje fizikalnega modela za a) električni in b) mehanski del*
Fig.4. *Physical model validation for a) electrical and b) mechanical part*

V danem primeru imamo 20-odstotno odstopanje pri električnem delu in 5-odstotno odstopanje pri mehanskem delu. Medtem ko je točnost mehanskega modela zadovoljiva, pa točnost električnega modela ni sprejemljiva za potrebe zaznavanja napak [4]. Sklepamo, da je tako veliko odstopanje posledica nemodelirane nelinearne magnetne karakteristike (npr. histereza, nasičenje jedra), ki je posledica izmeničnega napajanja motorja. Razlago v nadaljevanju poenostavimo tako, da obravnavamo le električni model motorja.

2.3 Kompenzacija odstopanja modela

Večjo občutljivost na napake lahko dosežemo s kompenzacijo odstopanja modela ([3] in [4]). Tu fizikalni model kombiniramo s sistemom mehkega sklepanja na podlagi adaptivnih nevronskih mrež NSSANM, opisanega v prejšnjem poglavju. Tako hkrati ohranimo pomen osnovnih parametrov fizikalnega modela, ki so potrebni pri morebitni izolaciji napak [4]. Glavni problem pri zaznavanju napak predstavljajo t.i. nestrukturirana odstopanja modela z neznanimi parametri, za katere ne poznamo fizikalnega ozadja. V tem primeru je za sprotno kompenzacijo v realnem času najprimernejši *vzporedni* hibridni model [9].

Princip kompenzacije odstopanja modela prikazuje slika 5. Potrebni vhodi v adaptivno mrežo so vstop procesa, izstop modela in odstopanje modela (ostanek). Med fazo učenja uporabimo dejansko odstopanje, med sprotno rabo pa uporabimo oceno odstopanja. V nasprotnem primeru bi se lahko izničilo tudi odstopanje zaradi napak v delovanju motorja, ki jih tako ne bi bilo mogoče zaznati.

2.4 Hibridni model

V danem primeru izberemo kot vhod v nevronsko mrežo vrednosti napetosti *u(t)*, toka *i(t)* ter vrtilne frekvence *ω(t),* izhod pa predstavlja odstopanje modela toka. Pri prvih poskusih

The results show an error-to-signal ratio of roughly 20% for the electrical part and 5% for the mechanical part. While the accuracy of the mechanical model is acceptable, the obtained electrical model is unacceptable for detection purposes [4]. It is assumed that such a big error is caused by the unmodelled non-linear magnetic characteristic (i.e., hysteresis, magnetic saturation) as the motor is driven by an AC voltage. For simplicity, only the electrical model will be elaborated.

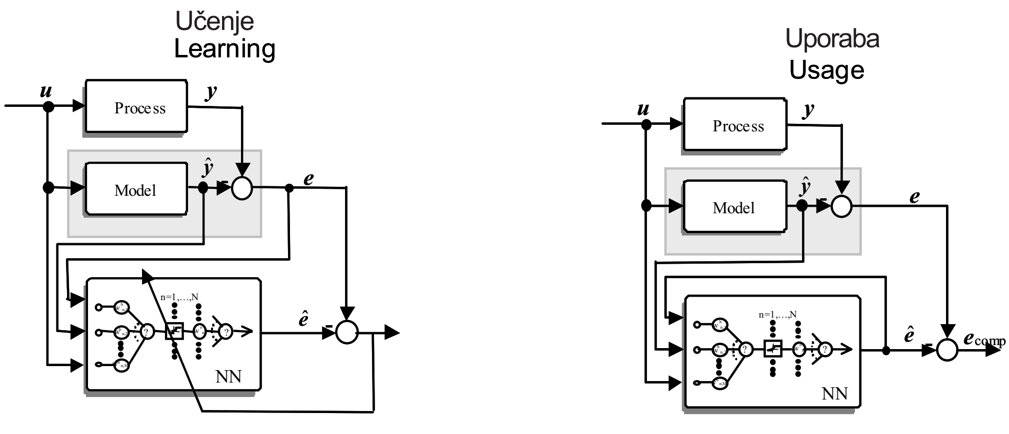
2.3 Compensation of the modelling error

To achieve a higher fault sensitivity, the compensation of the modelling error can be employed ([3] and [4]). This is done by combining the physical model with a black-box model based on ANFIS introduced in the previous section. By keeping the nominal model description, the physical parameters that are necessary for possible fault isolation are preserved [4]. The main problem of fault detection is caused by a non-structured modelling error with unknown parameters and an unfamiliar theoretical background. In this case, a *parallel* hybrid model seems suitable for online compensation in real time [9].

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

2.4 Hybrid model

In the given case, the supply voltage *u(t)*, the current *i(t)* and the rotational speed *ω(t)* were chosen as inputs to the adaptive network, while the modelling error of the current was chosen as the



Sl. 5. *Princip kompenzacije napake modela*
Fig. 5. *Principle of modelling-error compensation*

modeliranja smo uporabili tudi več zakasnjenih vhodov zaradi pričakovane nelinearnosti s spominom (histereza). Vendar smo dobili zadovoljivo točnost modela že s preprosto statično relacijo.

Za vsak vhod smo izbrali tri pripadnostne funkcije, kar nam da model NSSANM z naslednjimi lastnostmi:
- število vozlišč: 91
- število linearnih parametrov: 108
- število nelinearnih parametrov: 27
- število mehkih odločitvenih pravil: 27

Dobljeni hibridni model identificiramo v dveh korakih. Najprej identificiramo parametre fizikalnega modela z metodo najmanjših kvadratov. Nato izvedemo postopek učenja adaptivnih mrež (poglavje 1.2), da kompenziramo odstopanje nominalnega modela (en. 13).

output. Preliminarily, several delayed inputs were also considered due to the expected nonlinearity with memory (i.e., hysteresis). However, acceptable model accuracy was achieved with a 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 a simple least-squares method. Then, a learning procedure for adaptive networks (Section 1.2) is applied in order to compensate the errors resulting from the nominal model (Eq. 13).

3 DIAGNOSTIČNI REZULTATI

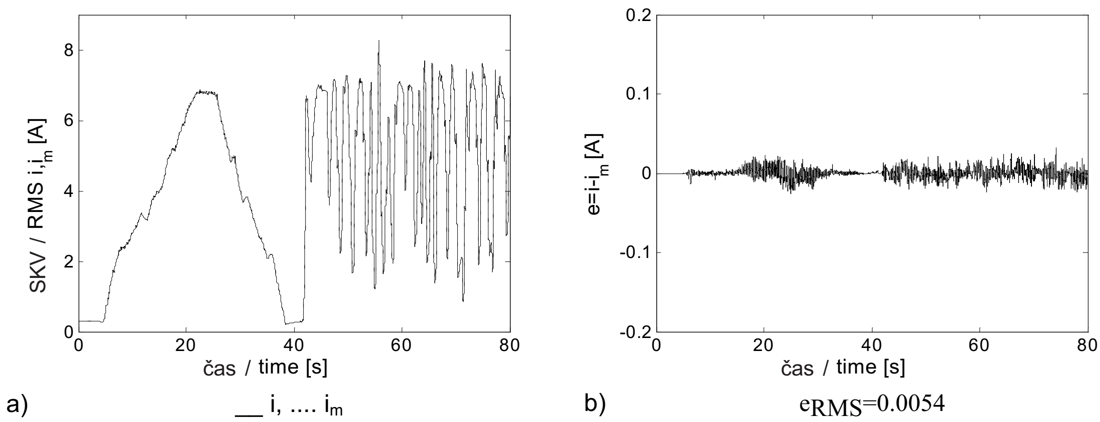
3 DIAGNOSTIC RESULTS

3.1 Vrednotenje

Vrednotenje modela je potekalo na množici 10 motorjev. Slika 6 prikazuje potek izhoda električnega dela enega izmed dobrih motorjev in ocene hibridnega modela ter pripadajoče odstopanje *e*.

3.1 Validation

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



Sl. 6. *Ujemanje hibridnega modela*
Fig. 6. *Validation of the hybrid model*

Vidimo, da dosežemo odlično ujemanje modela z dejanskim motorjem, saj je efektivno odstopanje manj kot 1% in je na sliki 6 a) praktično nevidno. Poudariti je treba, da identificiramo parametre modela le enkrat za izbrani tip motorja, zaznavanje napak pa poteka na osnovi ocene modela.

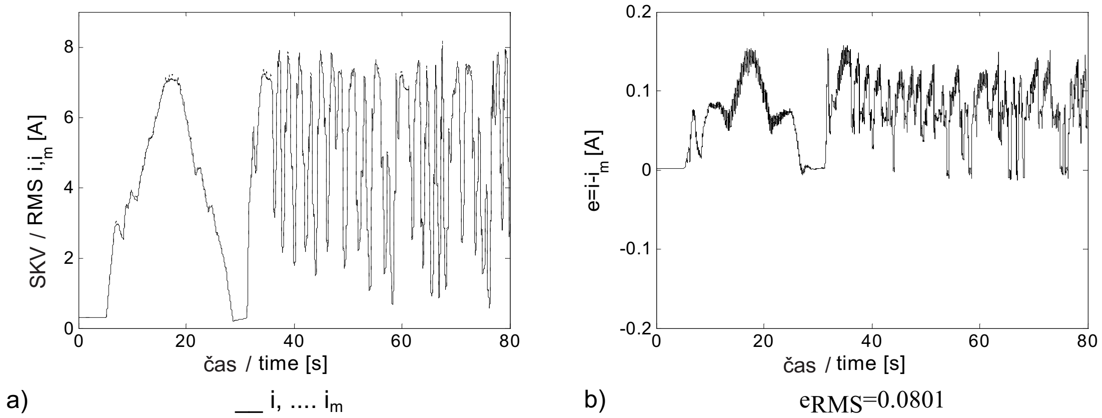
The results show that the error-to-signal ratio reduces to roughly less than 1% and is therefore practically invisible in Figure 6 a). It is important to note that the model parameters are identified only for each type of motor and that the estimated model is then used in fault detection.

3.2 Zaznavanje napak

V nadaljevanju isti hibridni model uporabimo na primeru motorja z okvaro na električnem delu (iskrenje ščetk). Obravnavamo le nenadne napake, saj je bil namen diagnostičnega sistema zaznavanje

3.2 Fault detection

The same hybrid model is further applied to the motor with a fault in the electrical part (sparking of the brushes). Only abrupt faults are considered, as the purpose of the diagnostic system was to detect



Sl. 7. *Ujemanje modela na motorju z okvaro*
Fig. 7. *Hybrid model applied to faulty motor*

prirojenih napak na koncu proizvodne linije. Slika 7 prikazuje ujemanje modela z dejanskim motorjem.

Vidimo, da se efektivno odstopanje poveča več kot 10-krat, kar omogoča zanesljivo zaznavanje napake motorja.

inherent faults at the end of the production line. The output is shown in Figure 7.

The results show that the model discrepancy increases more than 10 times and can therefore be used as a reliable feature for fault detection.

4 SKLEP

Predstavili smo zaznavanje napak elektromotorjev sesalnih enot z matematičnim modelom. Zaznavanje napak poteka na osnovi zakonov o ohranitvi energijske bilance sistema. Vsako odstopanje med izmerjenimi in ocenjenimi vrednostmi pomeni prisotnost napake. Zato vsako odstopanje modela neposredno vpliva na občutljivost na napake.

Da bi izničili vpliv nemodeliranih nelinearnosti, uporabimo princip kompenzacije odstopanja modela s pomočjo adaptivnih nevronskih mrež (NSSANM). Diagnostični rezultati na realnih napravah potrjujejo bistveno zmanjšanje odstopanja modela, kar omogoča večjo občutljivost na napake. Posledično se zmanjša tudi število lažnih alarmov in spregledanih napak.

Ob vsaki zamenjavi tipa motorja pa je treba poskrbeti za ustrezno vzbujanje, ki zajame celotno dinamično območje delovanja. Tudi sposobnost osamitve napak je omejena le na električni oz. mehanski del. Do določene mere lahko dosežemo večjo ločljivost z dodatno uporabo klasičnih metod ocenjevanja parametrov.

4 CONCLUSION

A model-based fault detection of vacuum-cleaner motors is presented. The fault detection relies on energy balance conservation laws. The discrepancy between the measured and the predicted values reflects the presence of a fault. Any modelling error directly affects the sensitivity to faults.

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

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

5 ZAHVALA

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