Shaft Misalignment Detection Using ANFIS for Speed Sensorless AC Drive with Inverter Output Filter

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Abstract: The aim of the paper is to present a diagnostic system for shaft misalignment detection. The diagnostic system is used in an adjustable speed sensorless induction motor (IM) drive with an inverter output filter. A nonlinear control algorithm and state observer were used in the motor control. Because the inverter output filter was installed in the drive, the control structure, as well as the estimation systems, were adequately changed. The adaptive neuro-fuzzy inference system (ANFIS) is used for shaft coupling fault detection. ANFIS is based on the analysis of the stator current, motor speed, and load torque processing. ANFIS uses only signals estimated from the state observers whereas observers calculate required variables only on the base of the inverter input voltage and two output current sensors. No additional special sensors are required. The proposed diagnostic system clearly indicates the shaft misalignment. The paper presents the model of the drive, control and estimation algorithms, as well as the diagnostic system. Whole drive and ANFIS fault indicator were verified by experiments for a 1.5 kW induction motor drive system.

INTRODUCTION

Misalignment in a motor drive system is a condition where the centerlines of coupled shafts do not coincide. This is one of the severe conditions that occur very frequently in motor drive systems and are most of the time responsible for drive failure [1]. Shaft misalignment effects negatively influences the rolling, sealing and coupling parts and can also produce eccentricity in the air-gap. The misalignment conditions are broadly classified as angular (offset) or parallel and combination of these two. If the misaligned shaft centerlines are parallel but not coincident, then the misalignment is said to be parallel or offset misalignment. If the misaligned shafts meet at a point but are not parallel, then the misalignment is classified as angular misalignment. Almost all misalignment conditions of motor drive systems seen in practice are a combination of these two basic types [1, 2]. The presented paper focuses on the angular misalignment which produces a bending moment on each shaft and generates a strong vibration at two times in the axial direction at both bearings, and of the opposite phase, leading to failure e.g. a gear box and bearings.

The diagnosis of misalignment conditions is mainly done using motor current signature analysis (MCSA), vibration analysis, and noise analysis [3-10]. The MCSA extracts the features of current using fast Fourier transform (FFT). The FFT analysis of stator current shows a significant increase in the amplitude of the components associated with the static and dynamic gap eccentricity [5-10]. The air gap eccentricity, bearing fault, and misalignment produces a current spectrum at frequencies given by $f_{mfr}$, and hence the FFT analysis may not be full proof in identifying the misalignment condition [3]. Furthermore, FFT analysis is not suitable when the motor is supplied from a variable frequency source because fundamental frequency varies in a wide range. There are also significant effects of loading in misaligned motor shaft, as the shaft will be highly stiff and the current spectrum will result in missing the important frequency components [5].

Artificial intelligence techniques are considered significantly in condition monitoring and fault diagnosis of electrical machines - review is in [21-23]. Neural network and fuzzy logic techniques have their own shortcomings as detailed in [22] and thus a specific combination of these two techniques known as Adaptive Neuro-Fuzzy inference system (ANFIS) have evolved as a better alternative solution [24]. The adaptive neuro-fuzzy inference system technique offers the best training feature of Neural Network and heuristic interpretation of the process results similar to Fuzzy logic theory thus providing a powerful tool that can be employed in conjunction with the condition monitoring and fault diagnostic applications. The use of ANFIS is growing in popularity in this niche application area and a significant amount of literature is available [25]-[28]. Mechanical fault diagnosis using ANFIS is also discussed in [29]-[31].

In industrial applications of PWM inverters the inverter output filters are widely used. The filters eliminate the destruction effects of the high dv/dt caused by modern transistors. The main unwanted effects are bearing degradation and motor efficiency decreasing. [11, 12]. Unfortunately the LC filters complicate motor control and variable estimation because the additional voltage drop and the phase shift of the voltage and current signals appear [13]. Therefore the sophisticated speed sensorless drives require some important changes in control as well as estimation structures [14-20]. It is especially important in speed sensorless drives as well as essential for diagnostic application of the observers.

In this paper, a voltage source inverter fed motor drive system with control of current, flux, torque and speed with a possibility for misalignment fault detection is presented. Previously authors have presented the initial diagnostic results in [36] where classical DFT analysis were
implemented. In this paper the ANFIS is used for fault indication instead of the conventional solutions e.g. MCSA. The used ANFIS is operating based only on estimated signals. In the investigated system, the inverter output LC filter for current and voltage smoothing is used. The parameters of this filter are taken into account during variable estimation and in the control scheme. Although a filter was installed, it was decided that only the preexisting sensors in the inverter be used. Because ANFIS also needs a load torque signal, the additional observer is used. The data collected in the experimental test bench are used to train the ANFIS and also used for the next fault classification and identification. The angular misalignment in the shaft is referred to as gear health in the presented results. The following presents the developed theory followed by experiments carried out.

**MOTOR AND FILTER MODELS DESCRIPTION**

The structure of the drive with LC filter is presented in Fig. 1.

![Fig. 1. AC drive with inverter and LC filter](image)

In the drive with IM and LC filters, both elements could be modeled by a differential equation description. It is typical to use these relations for further estimation procedure descriptions and used variables and parameters notation.

**Induction motor model**

Induction motor model in the stationary $\alpha\beta$ reference frame are given by [35-37] in per unit system:

$$d i_x / dt = a_1 i_x + a_2 \psi_r - ja_3 i_s + a_4 u_s ,$$  

(1)

$$d \psi_r / dt = a_s i_x + a_6 \psi_r + j a_5 \psi_r ,$$  

(2)

$$d \omega_r / dt = J_m^{-1} \left( L_m / L_r \right) \left[ \psi_{r^*} - T_L \right],$$  

(3)

$$i_s = \begin{bmatrix} i_{sa} \\ i_{sb} \end{bmatrix}, \quad \psi_r = \begin{bmatrix} \psi_{ra} \\ \psi_{rb} \end{bmatrix},$$  

$$u_s = \begin{bmatrix} u_{sa} \\ u_{sb} \end{bmatrix},$$  

(4)

where $a_1 = \left( R_m + L_m^2 / L_r \right) / \left( L_m / \psi_r \right)$, $a_2 = R_s L_m / \left( L_r / \psi_r \right)$, $a_3 = L_m / \psi_r$, $a_4 = L_r / \psi_r$, $a_5 = R_s / L_r$, $a_6 = R_s L_m / L_r$, $L_m$, $L_r$, $L_s$, $L_{m_0}$ are the motor parameters, $u_{sa}$, $i_s$, $\psi_r$ denote the stator voltage, stator current and rotor flux vectors, $T_L$ is motor load torque, $J_m$ is motor inertia.

**Inverter output filter**

The equations of the used LC filter are as follows [32]:

$$d u_f / dt = i_x / C_f,$$  

(5)

$$d i_f / dt = \left( u_f - R_i i_f - u_s \right) / L_i,$$  

(6)

$$i_c = i_f - i_s,$$  

(7)

$$u_s = R_i \left( i_f - i_s \right) + u_s,$$  

(8)

where: $u_{sa}$, $i_s$, $u_s$, $i_c$ are the filter input and output voltages and currents, respectively.

With the filter, the sinusoidal IM stator current and voltage waveforms are obtained - Fig. 2.

**CONTROL SYSTEM**

For controlling the drive the closed loop system was used. The motor control principle is a nonlinear algorithm known as a multi-scalar control method where four complex variables are regulated [34]:

$$x_1 = \omega_r \text{ - mechanical speed},$$  

(9)

$$x_2 = \psi_{ra} i_{\beta} - \psi_{r\beta} i_{sa} \text{ - motor torque},$$  

(10)

$$x_21 = \psi_{ra}^2 + \psi_{r\beta}^2 = \left| \psi_r \right|^2 \text{ - rotor flux square},$$  

(11)

$$x_{22} = \psi_{ra} i_{\beta} + \psi_{r\beta} i_{sa} \text{ - magnetizing component},$$  

(12)

Additionally, in control algorithms the decoupling relation are realized:

$$u_1 = w_0 \left( x_{s2} + a_2 x_{s2} \right) + m_1 \text{,}$$  

(13)

$$u_2 = w_0 \left( -x_{s1} x_{s2} - a_2 x_{s2} - a_6 \left( x_{s1}^2 + x_{s2}^2 \right) \right) + m_2 \text{,}$$  

(14)

where $m_1$, $m_2$ are and $u_1$, $u_2$ are the auxiliary variables used for stator commanded voltage $u_{sa}^{com}$ evaluation:

$$u_{sa}^{com} = \left( \psi_{ra} u_2 - \psi_{r\beta} u_1 \right) / \psi_r^2,$$  

(15)

$$u_{r\beta}^{com} = \left( \psi_{ra} u_1 - \psi_{r\beta} u_2 \right) / \psi_r^2.$$

(16)

Equations (9)-(16) transform the IM into a linear system, where mechanical and electromagnetic variables are controlled in the decoupled way.

Because the LC filter presence the multi-loop solution for motor and LC filter control are usually applied [15-18]. More details on the control solution are in [33].
ESTIMATION SYSTEM

In the IM drive the measured variables are two inverter output current and inverter supply voltage. Other controlled variables are estimated in the observer system [35]. Such a solution is typically known as a sensorless drive. In the observer structure the LC filter relations are included. The observer structure is as follows [36]:

\[
di 
\frac{d}{dt} = a_1 \dot{x} + a_2 x + a_3 \dot{\psi}_r + a_4 \psi_r + k_1 (i_1 - \dot{i}_1)
\]
(17)

\[
di 
\frac{d\dot{\psi}_r}{dt} = a_2 \dot{x} + a_3 \dot{\psi}_r + j x_2 + e_v
\]
(18)

\[
di 
\frac{d\dot{x}_2}{dt} = a_3 \dot{x} + a_4 \dot{\psi}_r + j \dot{x} + j k_4 (i_1 - \dot{i}_1)
\]
(19)

\[
di 
\frac{dS_{bf}}{dt} = k_b (S_b - S_{bf})
\]
(20)

\[
di 
\frac{d\dot{x}_c}{dt} = (i_1 - \dot{i}_1) C_1
\]
(21)

\[
di 
\frac{d\dot{x}_1}{dt} = (u_{ic}^c - a_1) L_1 + k_3 (i_1 - \dot{i}_1) + j k_4 (i_1 - \dot{i}_1)
\]
(22)

\[
\dot{x}_4 = c_1 \psi_r + c_2 \dot{\psi}_r + \dot{\psi}_r + \dot{\psi}_r
\]
(23)

where: \(\dot{\psi}_r\) is the motor electromotive force (EMF), \(k_1, k_2, k_3, k_4, k_5, k_6\) are the observer gains, \(S_b\) is the observer internal stabilizing component, \(S_{bf}\) is \(S_b\) are the filtered value and \(k_b\) is the inverse of \(S_b\) filter time constant.

The motor speed is estimated as follows:

\[
\dot{\theta} = \frac{\dot{\xi}_r + \dot{\xi}_p}{\dot{\psi}_r + \dot{\psi}_r}
\]
(26)

Deeper details on the observer system theory, tuning and stability were presented in [35] for drives without an LC filter and in [32, 33, 36] for drives with a filter.

In the proposed solution an additional observer was also used for load torque estimation. It was necessary for diagnostic algorithm where \(T_L\) is one of the ANFIS input. The torque observer has structure [36-37]:

\[
\frac{d\dot{L}_c}{dt} = \begin{bmatrix} 0 & -k_{L1} \end{bmatrix} \dot{L}_c + \begin{bmatrix} k_{L1} k_{L2} J_M & \dot{\psi}_r \end{bmatrix} \dot{L}_c + \begin{bmatrix} k_{L1} \end{bmatrix} \dot{\psi}_r + \begin{bmatrix} k_{L1} J_M & \dot{\psi}_r \end{bmatrix} \dot{L}_c
\]
(27)

\[
\dot{\dot{L}}_c = z_2 - k_{L2} J_M \dot{\psi}_r
\]
(28)

where: \(z = [z_1, z_2]^T\) is the load torque observer internal state variable, \(\dot{\psi}_r\) is the calculated motor electromagnetic torque, \(\dot{\psi}_r\) is the calculated motor load torque and \(k_1, k_2\) are the observer coefficients.

Motor speed appearing in (27)-(28), is taken from (26) whereas motor electromagnetic torque is calculated due to:

\[
\dot{\psi}_r = \dot{\psi}_r \dot{\psi}_r - \dot{\psi}_r \dot{\psi}_r
\]
(29)

The similar \(T_L\) calculation solution was earlier use by authors in traction drive [37].

EXPERIMENTAL SYSTEM

The presented drive system with the nonlinear control and the observers was tested by experiments. In the test bench 1.5 kW IM with PWM inverter was coupled with a dc generator. Between the inverter and motor, the LC filter was installed.

The test bench is presented in Fig. 3 and the related data in Table 1. Only the inverter output current sensors and inverter supply voltage sensor were used for control, estimation and for the diagnostic process. Other measured signals indicated in Fig. 3 were used only for the general purposed data acquisition.

In the test bench the machine mechanical coupling system faults were artificially generated. The mechanical misalignment was prepared by installing metal washers under the feet of loading machine as shown in Fig. 4.

The experimental system the drive was working with a nonlinear control in a sensorless mode of operation. Results of the drive tests were presented previously in [32, 33, 36] so in this paper only the results of the ANFIS are presented.
This section elaborates on the misalignment fault diagnostic using adaptive neuro-fuzzy inference system - ANFIS. The ANFIS fault indicator was used for the drive presented in the previous sections and tested using experimental data. Since the gear is affected the most, the misalignment is classified as gear health. So the gear health index in turn determines the angular misalignment in the shaft. For the purpose of fault classification, three inputs are chosen to train the ANFIS controllers:

- estimated load torque,
- estimated motor speed,
- and estimated stator current magnitude.

The current magnitude was calculated on the DSP board on the base of two measured inverter output currents.

The output of the ANFIS controller is the percentage of the gear health which ultimately refers to the misalignment. Good gear health refers to perfectly aligned shaft, fair health refers to the incipient misalignment condition or slightly but acceptable misaligned condition and bad health refers to visible misaligned condition. The gear health is heuristically defined as:

\[
\text{Gear health} = \begin{cases} 
0 \leq h \leq 40 & \text{Bad health} \\
40 \leq h \leq 70 & \text{Fair health} \\
70 \leq h \leq 100 & \text{Good health}
\end{cases} \tag{30}
\]

where \( h \) is the gear health index.

The block schematic of the experimental set-up is further shown in Fig. 5. Initially the drive was run in the system without fault – no misalignment - for speed ranging from 0.1p.u. to 1.0p.u. with resolution of 0.1p.u. The data of 500 samples of each signal were collected for the tested operating speeds using data acquisition card and stored in DSP control card and sent to the PC for analysis in Matlab/Simulink. These data points were finally used to train the ANFIS controller. Few more data points were collected at random speeds that were finally used for testing of the ANFIS controller. The data sampling time was chosen as 3.9 ms. The same set of experimental results were collected for misaligned conditions that were also used for the training and testing of the ANFIS controller.

The training data sets used are the raw data without any pre-processing which were collected from the experimental test bench. The ANFIS was trained off line for the healthy and faulty conditions. The fuzzy inference system was generated using sub-clustering algorithm with range of influence as 0.5, squash factor 1.25, accept ratio 0.5 and reject ratio equal to 0.15. The optimised ANFIS structure generated from Matlab/Simulink toolbox is presented in Fig. 6, whereas the corresponding membership functions for three inputs are presented in Fig. 7. The ANFIS structure shows three inputs which are estimated values of speed, torque and current magnitude. Also ten membership functions are created for each input of ANFIS. Ten membership functions thus generated for each input and correspondingly ten rule base were created. The rule bases are then multiplied by the appropriate weight function generated by the Matlab/Simulink toolbox. These weight functions were combined together to form one output which is the gear health index. The membership functions in Fig.7 are shown after proper training of ANFIS controller.
Fig. 7. ANFIS optimised membership function (normalised values): a) estimated load torque, b) current magnitude, c) estimated motor speed.

The surface created between the any two input parameters and outputs were obtained and are depicted in Fig. 8. The surface created in Fig. 8 clearly shows the effectiveness of the diagnostic tool proposed in the paper.

Finally the operation of the ANFIS controller was verified by giving random data for misaligned and non-misaligned conditions for different operating speed. The output of the ANFIS obtained during the tests is presented in Fig. 9. It is evident the by observing the output of the ANFIS controller the misalignment is easy to detect. More details on used ANFIS theory applied for bearings fault detection were presented in [38].

The range of the gear health is [-50, 150] or [-100 200] in the results as shown in Fig. 8. It is because the surface is plotted for all conditions with all possibilities, but the real health index will cover only the above mentioned boundaries in (30).

CONCLUSIONS

The main focus of the paper is to use ANFIS in the nonlinear speed sensorless control drives with LC filters for misalignment fault detection. The ANFIS fault indicator is based on the analysis of estimated speed, motor current, and torque. The data collected from the experimental test bench were used for off line training of ANFIS based diagnostic controller. The ANFIS was trained using raw data without any signal processing of the collected data. Testing the ANFIS was used for the off-line fault indication. However the ANFIS test presented the good effectiveness for fault diagnosis. Future works are oriented for ANFIS fault indicator on-line application.

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