Fuzzy Fault Detection for Permanent Magnet Synchronous Motor

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Abstract. In the transition to automated and automatic manufacturing an urgent problem is to increase the reliability of mobile robots (MR) and their drives, creation of devices to monitor the technical characteristics of MR, diagnose and predict the remaining resource. In spite of the high relevance of the diagnosing MR drives problem, there are no generally accepted methodology for diagnosing MR drives, criteria for selecting methods, parameters and volumes of diagnostics at present. An unsolved problem, related to the diagnosis of MR drives and the prediction of their residual life remains, is the development of methods that allow to carry out of automatic complex multiparametric diagnostics and prediction of the residual life using artificial intelligence methods. Effective fault detection and diagnosis can improve the reliability of the MR drive and avoid costly maintenance. In this paper a fault detection scheme for synchronous motors with permanent magnets based on a fuzzy system is proposed. The sequence current components (positive and negative sequence currents) are used as fault indicators and are set as input to the fuzzy fault detector. The expediency of the proposed scheme for determining of various types of faults for a synchronous motor with permanent magnets under various operating conditions is simulated using the SimInTech software.

1 Introduction

Three-phase drives based on high-power synchronous motors are widely used for mobile robots with high carrying capacity. The advantage of synchronous motors with permanent magnets (PMSM) is the absence of field windings on the rotor.

A number of approaches for online detection of electrical drive defects have been proposed in recent years [1], [2]. The model-based diagnostic concept is the most widely used approach due to the need for uninterrupted operation of mobile robot drives and increasing requirements for their reliability [3].

PMSM modeling is the first step in the development of diagnostic systems [4], [5]. Models show a complex relationship between parameters, accurate identification of a fault is very difficult. The accuracy of the drive model is limited due to its idealization. Environmental factors such as motor temperature and operational factors: speed and current may affect the fault signature [6]. Fault detection based on spectral analysis of vibration is

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considered in [7]. The disadvantages of this method are necessary to use the expensive high-precision vibration sensors.

The components of voltage and current imbalances are used to detect an inter-turn fault and are obtained from linear voltages and currents that are set as input data for a fuzzy fault detector [8]. A fault detection scheme for the PMSM drive, taking into account electrical defects such as stator resistance and inductance, is described in [9].

2 PMSM fuzzy logic fault detection and identification system

2.1 PMSM defects classification

PMSM defects such as follows: rotor defect, overload, defects in the mechanical and electrical parts of the motor, single-phase short-circuit to the housing, two-phase short-circuit to the housing, and combined defect.

Rotor defect (demagnetization)

For PMSM, the main defect of the rotor is a defect in the magnets or their degradation, which is the result of a pulsating load or a manufacturing defect. Demagnetization of the rotor causes vibrations, vibrations, abnormal noises, etc.

Overload (overheating)

PMSM overload as well as overcurrent leads to its overheating. The maximum operating temperature of the motor usually does not exceed 90 °C. High temperatures significantly reduce the service life of the engine, and prolonged exposure can cause it to break down.

Mechanical part defects

This type of defect is associated with a sudden change in the moment of inertia and coefficient of viscous friction, which can be caused by bearing defects, lack of lubrication, overload and eccentricity of the air gap. Defects in the mechanical part are characterized by excessive vibrations, which lead to incorrect operation of the motor, and in the future can lead to its breakdown.

Electrical part defects

Defects in the electrical part mainly occur due to abnormal changes in the resistance and inductance of the stator winding, which leads to their overheating.

Single-phase enclosure fault

This situation occurs when any of the phases is closed to the motor housing. In this case, the short-circuit current increases, the interfacial voltage at the fault point tends to zero, and the phase voltages make up half of the motor supply voltage. Due to the voltage drop, the motor speed and electromagnetic torque are significantly reduced.

Two-phase enclosure fault

Occurs when any two phases of the motor are closed to the housing. As in the case of a single-phase fault, the short-circuit current increases strongly, and the phase-to-phase voltage at the fault point tends to zero.

Combined defect (overload and rotor defect)

Overloading can physically affect on the rotor shaft, causing it to break or crack, which in turn will cause a decrease in magnetic flux, that will reduce the efficiency of the motor.

2.2 Fuzzy fault detection system

A block diagram of the proposed system for detecting and identifying PMSM faults based on fuzzy logic is shown in Figure 1. Fault identification is based on an assessment of the

linear current imbalance [8]. An imbalance of the stator winding creates positive and negative current imbalances in the motor, which are used as fault indicators.

The positive I_{a1} and negative I_{a2} current imbalances are calculated from the linear currents of phases a, b, c as follows:

$$I_{a1}=1/3\cdot(I_a+aI_b+a^2I_c) \tag{1}$$

$$I_{a2}=1/3\cdot(I_a+\alpha^2I_b+aI_c) \tag{2}$$

where $\alpha=-0.5+j0.866$ and $\alpha^2=-0.5-j0.866$.

The components of imbalances are affected in a certain way by each of the defects. Then fault is identified using a fuzzy output system. Possible faults are modeled and detected using fuzzy logic in the SimInTech simulation environment.

Fig. 1. Block diagram of fuzzy fault detection system

The model-based fuzzy fault detection system consists of 3 main components:

- 1.PMSM-based electromechanical drive model;
- 2.Current imbalance calculation module (calculates positive I_{a1} and negative I_{a2} current imbalances);
- 3.A fuzzy fault detector module (identifies an motor defect).

The system is used to generate positive and negative current imbalances calculated from linear currents in the operating and faulty motor states. The calculated unbalances are used as input parameters for the fuzzy system.

2.3 PMSM fault modeling

The model of investigated electromechanical drive of mobile robot with fuzzy detection and fault identification system in SimInTech software is shown in Figure 2.

The PMSM model is Balt Systems KM-08-02.0-030 (specification in Table 1). The moment of inertia of the external mechanical load $J=390\text{ kg}\times\text{cm}^2$.

Table 1. PMSM specification

Parameter	Value
Stator phase inductance (Ls)	0.0053 Gn
Stator phase resistance (Rs)	1 Om
Rotor flow coupling (ψ)	0,4 Wb
Rotor moment of inertia (J)	2 $\text{kg}\times\text{cm}^2$
Coefficient of viscous friction (Bm)	0.5 $\text{N}\times\text{m}\times\text{s}$

Fig. 2. Model of electromechanical drive based on PMSM

The normal state of PMSM are presented on figures 2 (a-c).

Fig 3. Diagram of motor (serviceable state): a) phase currents; b) positive current imbalance; c) negative current imbalance;

The PMSM fault simulation was carried out as follows^

Overload (overheating)

Overload is modeled by changing the shaft load (T_L) from 100% to 200% of the rated load.

Rotor demagnetization

Rotor failure is modeled by a reduction in flow (ψ) to 25% of the nominal value.

Mechanical part defect

A mechanical failure is modeled by a change in J and B_m from 100% to 200% of the nominal values.

Combined defect (overload and rotor defect)

The combined defect is modeled by simultaneously reducing the flow (ψ) to 25% of the nominal value and changing the shaft load (T_L) from 100% to 200% of the nominal.

3 PMSM fuzzy fault detector

To ensure the accuracy of the PMSM fault identification system is recommended to assign an odd number of partitioning terms to each variable. The range of changes in the linguistic variables "positive current imbalance" I_{a1} is divided into eleven sets, "negative current imbalance" I_{a2} - into thirteen sets, and the linguistic variable "malfunction" – into eight on a base of experimental data obtained as a result of modeling,

It is necessary to define the ranges of changes in input and output variables when defining linguistic variables, After that, the range of changes in each variable is divided into sets, and it is necessary to choose the type of membership function.

In most of the works devoted to the development of fuzzy diagnostic systems, triangular functions are used as membership functions, due to the high speed of operation and good accuracy.

Thus, to describe the input variable I_{a1} applies fuzzy variable with eleven triangular terms: I_{a1_1} , I_{a1_2} , I_{a1_3} , I_{a1_4} , I_{a1_5} , I_{a1_6} , I_{a1_7} , I_{a1_8} , I_{a1_9} , I_{a1_10} , I_{a1_11} ; input variable I_{a2} - fuzzy variable with thirteen triangular terms: I_{a2_1} , I_{a2_2} , I_{a3_3} , I_{a3_4} , I_{a3_5} , I_{a3_6} , I_{a3_7} , I_{a3_8} , I_{a3_9} , I_{a3_10} , I_{a3_11} , I_{a3_12} , I_{a3_13} .

For linguistic descriptions of the output variable is a fuzzy variable with eight triangular terms: serviceable (S), overload (OL), rotor defect (RD), mechanical part defect (MD), electrical parts defect (ED), a single-phase circuit to the housing (SC), two-phase circuit to the housing (DC), a combined defect (defect of the rotor and overload) (CD).

It is necessary to reduce the signals to the range $[-1, 1]$ in digital systems by using the input signal normalization and output signal denormalization procedures. The normalization coefficients K_{Ia11} , K_{Ia22} for the input variables are determined based on the maximum possible values of positive and negative current imbalances obtained during modeling for the corresponding type of PMSM. The denormalization coefficient K_{FAULT} for the output variable is determined in such a way as to provide an integer value of the corresponding fault in order to simplify the visual perception of diagnostic information.

Positive current imbalance:

$$K_{Ia1} = 1/\max|I_{a1}| \quad (3)$$

Negative current imbalance:

$$K_{Ia2} = 1/\max|I_{a2}| \quad (4)$$

Output variable:

$$K_{FAULT} = 7 \quad (5)$$

The following values were used to assign the boundaries of the ranges of linguistic variables: positive Ia1 and negative Ia2 current imbalances - from 0 to maximum (current with a two-phase short-circuit to the housing).

The values of the normalizing coefficients are shown in Table 2.

Table 2. Normalization coefficients

Normalization factor	Value
K_{Ia2}	0.0001639
K_{Ia2}	0.0001639
K_{FAULT}	7

The ranges of changes in linguistic variables are shown in Tables 3-5.

Table 3. Ranges of changes in input linguistic variables for Ia1

	Positive current imbalance Ia1	Corresponding PMSM fault
Ia1_1	0; 0.00000328	S
Ia1_2	0; 0.000006884	RD, S
Ia1_3	0.000003442; 0.000007458	OL, SC
Ia1_4	0.000005737; 0.000006719	RD
Ia1_5	0.000006228; 0.000008196	S
Ia1_6	0.000006228; 0.000008428	MD
Ia1_7	0.000007328; 0.00001095	CD, ED, MD
Ia1_8	0.00000914; 0.0001121	SC
Ia1_9	0.00006064; 0.00007376	ED
Ia1_10	0.0000672; 0.000981	OL
Ia1_11	0.000524; 1	DC

Table 4. Ranges of changes in input linguistic variables for Ia2

	Negative current imbalance Ia2	Corresponding PMSM fault
Ia2_1	0; 0.00000009834	S
Ia2_2	0; 0.0000005518	S
Ia2_3	0.0000002759; 0.0000004125	S
Ia2_4	0.0000003442; 0.000001065	MD
Ia2_5	0.0000007212; 0.0009113	OL
Ia2_6	0.000004917; 0.00001147	SC
Ia2_7	0.000008195; 0.000017005	RD
Ia2_8	0.0000126; 0.00003002	RD, ED
Ia2_9	0.00002131; 0.00003441	S
Ia2_10	0.00002786; 0.00009342	SC
Ia2_11	0.00006064; 0.0001786	CD, OL
Ia2_12	0.0001196; 0.0005504	OL
Ia2_13	0.000335; 1	DC

Table 5. Ranges of changes in output linguistic variables

Fault	Value
Serviceable (working condition, no faults)	0; 0.143
Rotor defect	0; 0.286
Overload	0.143; 0.429
Mechanical part defect	0.286; 0.572
Electrical part defect	0.429; 0.715
Single-phase short circuit to the housing	0.572; 0.858
Two-phase short circuit to the housing	0.715; 1
Combined defect	0.858; 1

If a PMSM fault is detected, it requires an immediate shutdown of the mobile robot's drive, otherwise it may fail.

The degree of belonging of this variable is equal to 1 when a linguistic variable goes out of range,

The rules database for the fault detector block based on the ranges of splitting linguistic variables and the ranges corresponding to faults.

Rules are drawn up based on variations in the values of current imbalances for different types of faults using expert knowledge.

Rules are formed by the type IF ... AND ..., THEN ...

Here are some of them:

– if the positive current imbalance Ia1 is equal to Ia1_2, and the negative current imbalance Ia2 is equal to Ia2_7, then the robot drive is faulty (rotor defect).

Similarly, the rules can be formulated for other input values.

The final database of fault detector rules with fuzzy output, which includes 32 production rules, is shown in Table 6.

Table 6. Fault detector rule base

Malfunction	Positive current imbalance Ia1	Negative current imbalance Ia2
Serviceable (working condition)	Ia1_1, Ia1_2, Ia1_5	Ia2_1, Ia2_2, Ia2_3, Ia2_9
Rotor defect	Ia1_2, Ia1_4	Ia2_7, Ia2_8
Overload	Ia1_3, Ia1_10	Ia2_5, Ia2_11, Ia2_12
Mechanical part defect	Ia1_6, Ia1_7	Ia2_4
Electrical part defect	Ia1_7, Ia1_9	Ia2_8
Single-phase enclosure fault	Ia1_3, Ia1_8	Ia2_6, Ia2_10
Two-phase enclosure fault	Ia1_11	Ia2_13
Combined defect	Ia1_7	Ia2_11

The formulated rule base describes all possible combinations of input linguistic variables and the corresponding value of the output variable. This approach eliminates the possibility of uncertainty in the solution of the fuzzy inference system.

Fuzzy output is performed by Mamdani type.

Detected faults causing the output linguistic variable “Fault” are classified as follows:

1. Fault=0 - input variables Ia1, Ia2 correspond to the good motor condition;
2. Fault=1 - input variables Ia1, Ia2 correspond to the rotor defect condition;
3. Fault=2 - input variables Ia1, Ia2 correspond to the motor overload condition;
4. Fault=3 - input variables Ia1, Ia2 correspond to the condition of motor mechanical defect;
5. Fault=4 - input variables Ia1, Ia2 correspond to the condition of motor electrical

defect (change of R_s and L_s);

6. Fault=5 - input variables I_{a1} , I_{a2} correspond to the condition of a single-phase short circuit to the motor housing;

7. Fault=6 - input variables I_{a1} , I_{a2} correspond to the condition of a two-phase short circuit to the motor housing;

8. Fault=7 - input variables I_{a1} , I_{a2} correspond to the condition of a combined motor defect.

4 Conclusion

The main defects of synchronous motors with permanent magnets are considered: a defect of the rotor (magnet), defects in the mechanical and electrical parts of the motor, a single-phase short-circuit to the housing, a two-phase short-circuit to the housing, and a combined defect. Their influence on the diagnostic parameters of the engine is revealed.

A system for detecting and identifying faults in synchronous motors based on fuzzy logic has been developed by evaluating current imbalances. The simulation of motor failures and the evaluation of changes in its diagnostic parameters are carried out.

References

1. G.B. Kliman, W.T. Premerlati, R.A. Roegl, D.A. Hoeweler, *A new approach to on line fault detection in AC motors*, IEEE Conference on Industry Applications, v.1, pp. 687-693 (1996)
2. J. Sottiled, J.K. Kohler, *An on-line method to detect incipient failure of turn insulation in random-wound motors*, Proceedings of IEEE Transactions on Energy Conversion, v. 4(8) (1993)
3. J. Penman, H.G. Sedding, B.A. Lloid, W.T. Fink, *Detection and location of inter-turn short circuits in the stator windings of operating motors*, Proceedings of IEEE Transactions on Energy Conversion, v. 4(9), pp. 652-658 (1994)
4. H. Jiang, R. Aggarwal, G. Weller, S. Ball, L. Denning, *A new approach to synchronous generator internal fault simulation using combined winding function theory and direct phase quantities*, Ninth International Conference on Electrical Machines and Drives, pp. 105-111 (1999)
5. G.M. Joksimovic, J. Penman, *The detection of inter-turn short circuits in the stator windings of operating motor*, IEEE Transactions on Industrial Electronics, v. 5(47), pp. 1078-1084 (2000)
6. Amol S. Kulkarni, *Development of a technique for on-line detection of shorts in field windings of turbine-generator rotors: circuit design and testin*, IEEE Transactions on Energy Conversion, v. 1(15), pp. 8-13 (2000)
7. W.S. Tommy, Tan Hong-Zhou. *HOS-based nonparametric and parametric methodologies for machine fault detection*, IEEE Transactions on Industrial Electronics, v. 5(47), pp. 1051-1059 (2000)
8. Dawei Xiang, Li Ran, Peter J. Tavner, Schunchang Yang, *Control of doubly fed induction generator in a wind turbine during grid fault ride-through*, IEEE Transaction on Energy conversion, v. 3(21), pp. 652-662 (2006)
9. Li Liu, David A. Cartes, *On-line identification and robust fault diagnosis for nonlinear PMSM drives*, Proceedings of the American Control Conference, v. 3, pp. 2023-2027 (2005)