Diagnosis of Speed Sensor Failure in Induction Motor Drive

F. Zidani[1], D. Diallo[2], *Senior Member IEEE*, M.E.H. Benbouzid[3], *Senior Member IEEE*, Eric Berthelot[2]
[1]Laboratoire LSPIE, Electrical Engineering Department, University of Batna
[2]Laboratoire de Génie Electrique de Paris (LGEP)/ SPEE Labs, CNRS UMR 8507 ;
Supélec, Univ Pierre et Marie Curie P6, Univ Paris Sud P11, Plateau du Moulon, 91192 Gif-Sur-Yvette, France
E-mail: ddiallo@ieee.org
[3]Laboratoire d'Ingénierie Mécanique et Electrique (LIME), University of Western Brittany
IUT de Brest, Rue de Kergoat – BP 93169, 29231 Brest Cedex 3, France

***Abstract* - A large number of adjustable – speed drives in industry and emerging applications such as automotive (EV or HEV) require high dynamic performances, robustness against parameter variation and also reliability. parameter detuning and mechanical speed sensor faults lead to a deterioration of the performances and even to instability. therefore condition monitoring is becoming mandatory in those sensitive applications.**
the objective of this contribution is to study the feasibility of detection and diagnosis of the mechanical speed sensor faults in an induction motor drive. using knowledge of the motor condition, the proposed technique based on fuzzy logic is applied to discriminate load and parameter variations from the speed sensor faults. both simulation and experimental results are presented in terms of accuracy in the detection of speed sensor faults and knowledge extraction feasibility.

I. Introduction

The induction machines are work horse of modern industries because of various technical and economical reasons. But these machines face various stresses during operating conditions which may lead to failures. A large number of adjustable speed drives (ASD) in industry and emerging applications such as automotive (EV or HEV) require high dynamic performances, robustness against parameter variations and also reliability. However the ASD are very sensitive to faults which may occur within the power converter, the electrical and mechanical components of the machine but also to the mechanical speed sensor. Hence the condition monitoring is becoming mandatory in sensitive applications like automotive for example [1-7]. Moreover on-line fault diagnosis technology of incipient faults for induction drives is rapidly emerging to avoid the unpredictable failure [1]. Different invasive and non invasive approaches for motor incipient fault detection/diagnosis have been reported [11-15]. Many of the motor incipient fault detection/diagnosis schemes can be applied non invasively on-line without the need of expensive monitoring equipment by using a microprocessor. With proper monitoring and fault/diagnosis schemes the incipient faults can be detected in their early stages. Thus maintenances and downtime expenses can be reduced and reliability can be improved.

The indirect field oriented control (IFOC) is the most common control method for implementing high performance induction motor drive [8-9]. In general in the IFOC technique the shaft speed, that is usually measured, and the slip speed calculated from the machine equations are added to find the rotor flux vector position which is a critical issue. Therefore a close look is required on parameter variations and speed sensor fault which should lead to the controller detuning and even to the instability of the drive.
Parameter variations are usually tracked by adaptive mechanisms using additional sensors (stator temperature for example) or specific algorithms based on weak assumptions like no saturation in the core. The drawbacks are an increase of the computational burden and a low accuracy without a significant benefit in parameter adaptation.
On the other hand the mechanical sensor defect leads to a wrong computation of the rotating reference frame. As a consequence, depending on the torque to rotor flux ratio the torque control is detuned and this may lead to a instability if the deviation angle between the machine reference frame and the controller one is above a certain limit.
Hence one should pay attention to the deterioration of the mechanical speed sensor.

Fuzzy logic technology can be used to provide inexpensive but effective fault detection mechanism by an adequate analysis of the recorded data [16-19]. Fuzzy logic technique is easy to extend and modify by the incorporation of new data or information. Based on measurement data this approach may aid in data management for fault diagnostics purpose. Using knowledge of the motor condition, the proposed technique is applied to separate machine variations parameters effects and sensor position faults.

The paper is organized as follows. In section II, the experimental bench under test is described and some results are

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presented to validate the IFOC performance in normal operating condition, namely without parameter detuning or mechanical sensor fault. In section III, the data collected from numerous experiments with parameter detuning and angle deviation are analyzed to extract the knowledge which is introduced in the fuzzy detection block presented in section IV. The results of the detection block are presented in section V and eventually a conclusion is made.

II. DESCRIPTION OF THE EXPERIMENTAL SETUP

Fig. 1 shows the experimental setup. The squirrel-cage induction motor and inverter data are given in the Appendix. The currents flowing in the stator windings are measured with two Hall Effect current sensors and a 4098 points pulse incremental encoder is used as position sensor. The IFOC is implemented on a dSpace® 1103 board using the Matlab-Simulink® software package. Fig. 2 shows the speed reversal tracking and the rotor flux module at rated load. This establishes the performances of the drive.

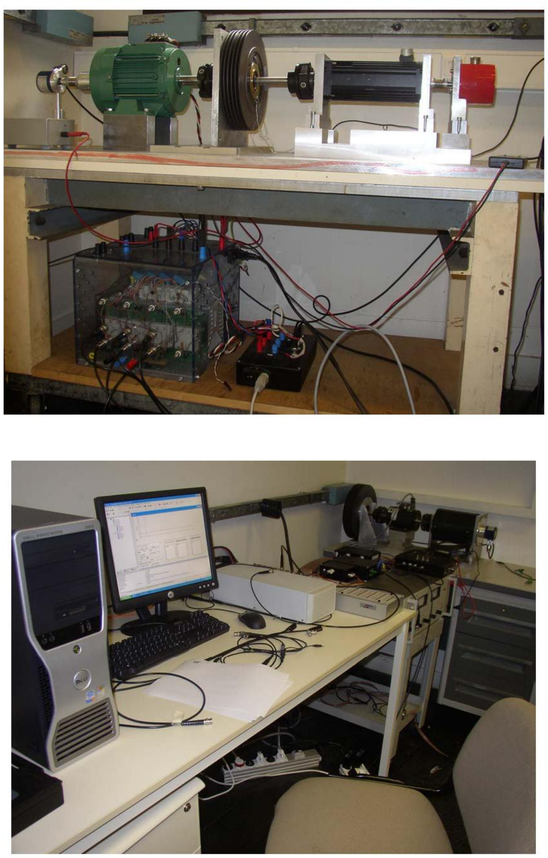


Fig.1: Experimental setup

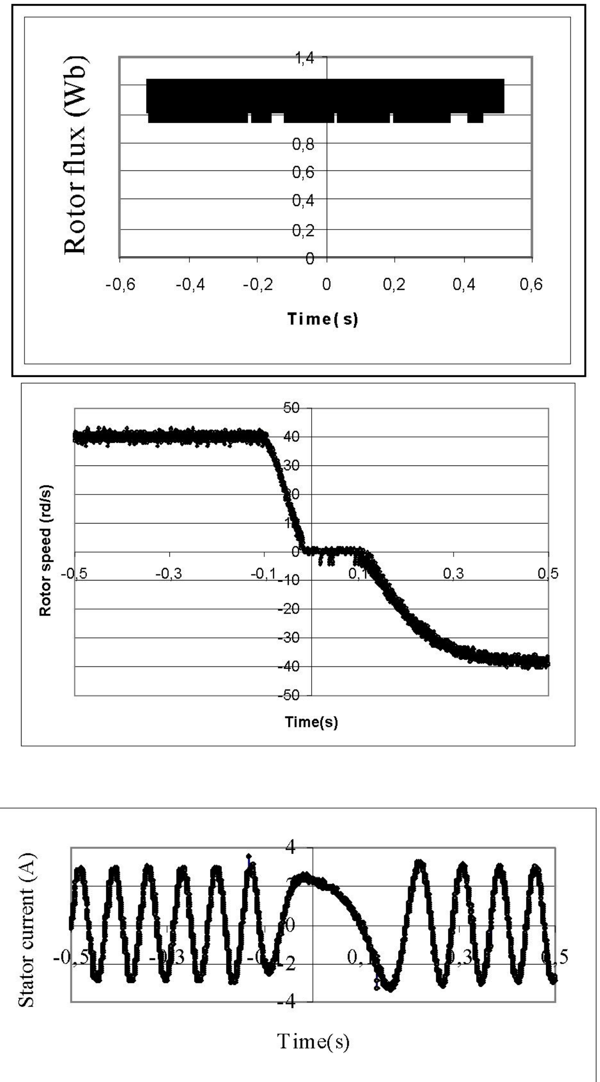


Fig.2. Rotor flux, rotor speed and stator current at rated load.

III. DATA ANALYSIS

In this section the rotor speed and stator current evolutions are analyzed when a parameter variation or a speed sensor fault occur at different operating points. The issue is to be able to discriminate those two effects. Therefore, the sensitivity of the IM has been studied to the variations of Rr and the stator angle deviations $\Delta\theta_S$.

A) *Machine parameter sensitivity*

During the tests five variations of rotor resistance are considered at steady state. Table 1 summarizes the results illustrating the transient behavior of speed variation $\Delta\Omega_{transient} = \left|\Omega_{ref} - \Omega_{transient}\right|$ and current error

$\Delta I_{s-transient} = \left| I_{sref} - I_{stransient} \right|$ for four operating points. The transient analysis examines the error $\Delta\Omega_{transient}$ and $\Delta I_{s-transient}$ in response to the parameter variation. The reference value corresponds to the nominal case in steady state.

TABLE 1

Experimental Data: *Parameter sensitivity"* **Rotor resistance variation"**

ΔR_r (%)	Ω_{ref}=5rd/s		Ω_{ref}=10 rd/s		Ω_{ref}=40 rd/s		Ω_{ref}=60 rd/s	
	$\Delta\Omega_{transie}$%	$\Delta I_{s-transi}$%	$\Delta\Omega_{transie}$%	$\Delta I_{s-transi}$%	$\Delta\Omega_{transie}$%	$\Delta I_{s-transi}$%	$\Delta\Omega_{transi}$%	$\Delta I_{s-transi}$%
20%	32	13.24	37	11.5	4.62	1.48	0.016	0.21
40%	49	27.02	42.5	15	10.87	12.97	0.016	0.21
60%			53.7	25	13.42	22.57	0.016	0.21
80%			78.7	35.5	54.67	31.48	0.016	0.21
100%			98.7	50	69.7	46.59	13.55	10.86

B) Speed sensor failure analysis: sensitivity to stator angle variation

The mechanical sensor fault is emulated by introducing in the IFOC algorithm different angle variations as an error $\Delta\theta_s$ in the determination of the rotor flux vector at steady state. The rotor flux and the electromagnetic torque are kept constant. Table 2 summarizes the collected experimental data $\Delta\Omega_{transient}$ and $\Delta I_{s-transient}$, the speed and current variations and the deviation $\Delta\theta_s$ for four different speeds.

TABLE 2

Experimental data: Speed sensor fault analysis

	Ω_{ref}=5rd/s		Ω_{ref}=10 rd/s		Ω_{ref}=40 rd/s		Ω_{ref}=60 rd/s	
$\Delta\theta_s$ (°)	$\Delta\Omega_{transi}$ %	$\Delta I_{s-trans.}$ %	$\Delta\Omega_{transi}$%	$\Delta I_{s-trans.}$%	$\Delta\Omega_{transi}$%	$\Delta I_{s-transi}$%	$\Delta\Omega_{transi}$%	$\Delta I_{s-transi}$%
-2	144.2	65.96	91.3	66.66	11.12	162.25	11.41	17.98
-1	108.4	46.98	66	27.38	7.07	50	7.25	15.02
-0.5	108.6	19.57	56.8	26.78	5.55	23.75	5.61	8.86
0	0	0	0	0	0	0	0	0
0.5	133.2	13.55	68.7	16.07	4.4	11.25	2.88	37.9
1	136.2	18.67	70.5	23.8	5.22	42.25	3.75	53.94
2	136.2	28.31	100.5	5.11	7.2	141.25	4.16	58.12

It is found that the largest values of $\Delta\Omega_{transient}$ and $\Delta I_{s-transient}$ are due to stator angle variation. This analysis and the data collected will be used in the design of the diagnosis procedure which is described in the following paragraph.

IV. FUZZY BLOCK DESCRIPTION OF SPEED SENSOR FAULTS

Fuzzy systems rely on a set of rules. These rules, while superficially similar, allow the input to be fuzzy (i.e., more like the way humans tend to express their way of thinking). Thus, a power engineer might refer to an electrical machine as "somewhat secure" or a "little overloaded." This linguistic input can be expressed directly by a fuzzy system. Therefore, the natural format greatly eases the interface between the engineer's knowledge and the domain expert. Furthermore, infinite graduations of truth are allowed, a characteristic that accurately mirrors the real world, where decisions are seldom "crisp"

The processes of speed sensor defects detection can be divided into four blocks:

- The data acquisition.
- The signal conditioning as applied to measured quantities to provide the input quantities to the evaluation method.
- The evaluation method is the fault detection technique based on fuzzy logic.
- The last block is fault assessment which provides an indication of the fault and its severity.

In this work a fuzzy system is used to strictly tie the operating conditions of the motor with the diagnosis that can be given by examination of the data analysis given in § III.

The inputs of the fuzzy evaluation block are chosen and are defined as $e_1 = \left|\Omega_{ref} - \Omega(k)\right| and\, e_2 = \left|I_{sref} - I_s\right|$.

The internal structure of this block is chosen similar to that of a fuzzy logic controller (fuzzification, inference engine and defuzzification). Both errors are normalized by dividing with the respective gains factors. For the purpose of this study, the fuzzy evaluation block output is the fault severity ***"FS"*** of the speed sensor. The selected membership functions are based on the previously collected experimental data. The amplitudes of the input variables have been defined as: *ZE*: zero, *L*: light, *M*: Medium, *H*: high and *VH*: Very high.

Fuzzy sets associated to the output have been defined as: *NF*: no fault (fault severity is considered as insignificant/negligible), *LF*: light fault, *MF*: Medium fault and *HF*: High fault.

TABLE 3
Rule base of fuzzy detection block

e_1 / e_2 *FS*	L	M	H
ZE	*NF*	*NF*	*NF*
L	*NF*	*NF*	*NF*
M	*NF*	*NF*	*NF*
H	***MF***	*NF*	***HF***
VH	***HF***	***LF***	*NF*

As illustration**:**

If (e_1 is *L/M/H* and e_2 is *ZE*) then *FS* is *NF:* This case corresponds in our experiment to load variation effects.

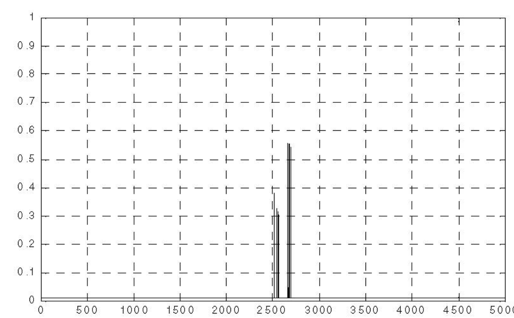
If (e_1 is *L/M/H* and e_2 is *L*) then *FS* is *NF.* This case corresponds in our experiment and according to data analysis to parameter variation effects.

If (e_1 is *H* and e_2 is VH) then *FS* is *NF.* This case corresponds in our experiment and according to data analysis to machine acceleration/deceleration.

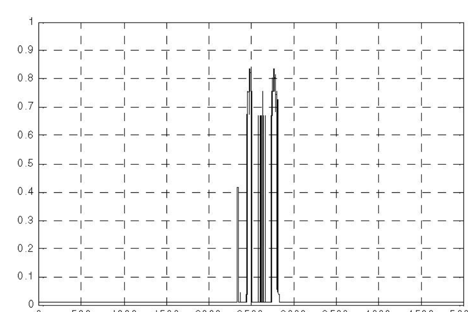
If (e_1 is L and e_2 is VH) then *FS* is *HF.* This case corresponds in our experiment and according to data analysis as a severe fault of the speed sensor.

V. FUZZY APPROACH VALIDATION

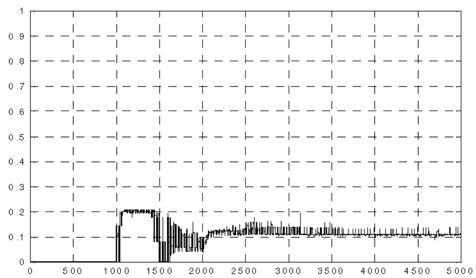
To evaluate the diagnosis method a deviation of $\Delta\theta_s = +2°$ or $\Delta\theta_s = -1°$ is considered. Fig. 3 shows the fuzzy output (fault severity *FS (%)*). The diagnosis gives a high (*HF*) fault severity (*FS* ≅ 80%) for the first case and a medium severity index in the second case (*FS* ≅ 50%). It can be noticed on Fig 3.c that when a rotor resistance variation $\Delta R_r = 75\%\ R_{rnom}$ is considered, the fault severity decreases significantly (*FS* ≅ 20%) and can be taken as *NF.*



a) Δθs = + 2°



b) Δθs = - 1°



c) $\Delta Rr = 75\% \ R_{rnom}$

Fig. 3. Fuzzy output of the detection block (*FS*).

VI. CONCLUSION

This paper has demonstrated that it is feasible to detect a speed sensor failure and moreover to discriminate it from parameter detuning effects on the drive performances. The proposed technique uses available system variable signals such as stator current and motor speed. The experimental results are very promising. On the other hand, the fuzzy validation approach is simple and easy to implement.

The proposed scheme is recommended for application when detection and isolation of speed sensor fault is preferable since it keeps the drive partially operative. This is the case of fault tolerant controllers in sensitive applications where a high level of reliability is mandatory like transportation systems.

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APPENDIX

INDUCTION MOTOR PARAMETERS

Rated values: Power1.1kW, Voltage (Δ/Y) 220/380V, Current (Δ/Y)4.7/2.7 A, Speed 1400 tr/min

f_s =50 Hz, ϕ_{snom},= 1.22 Wb, C_{rnom} =7 Nm

Parameters: Rs= 8 Ω, R_r =4 Ω, L_s = 0.47 H, σ = 0.075, J= 0.06 Kg.m^2, f = 0.04 Nm.s