Neuro-fuzzy diagnosis in final control elements of AC motors

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***Abstract*— The on-line diagnosis of an electrical drive is the first step towards the application of an effective predictive maintenance plan on such electrical machines. This paper applies neuro-fuzzy logic to induction motors condition monitoring. The analysis of residual features corresponding to instrumentation faults of induction motor lead to the design of faults classification system. The training set is obtained by a faulted machine dynamical model as simulator. Two neuro-fuzzy structures will be conceived to learn the exact input-output relation of the fault detection process for induction motor using measured data. The first neuro-fuzzy architecture maps the residuals into two classes: a one of fixed direction residuals and another one of faults belonging to velocity sensor. The second adaptive neuro-fuzzy network will be able to provide updated membership functions of the sets of fixed oriented residuals that better describe the fault diagnosis map. The preliminary results show that neuro-fuzzy logic can be used for accurate induction motors fault diagnosis if the input data are processed in an optimized way.**

I. Introduction

Failure may cause large amount of loss. Therefore, fault diagnosis system is very important for safe operation and preventing rescue. Recent progress in the field of diagnostics of electric drives is a result of broadly conceived basic research carried out over many years. Initial studies involved mainly theoretical bases of diagnostics of electric motors, power electronics converters and mechanical elements of motors [1],[2].

In an industrial control system a fault may occur in the process components, in the control loop (controller and actuators) and in the measurement sensors for the input and output variables. Broadly, the task of diagnosis concerns with detection of process behaviour deviations from normal trajectories (nominal operating points), identification of abnormal states, and prescription of the appropriate reconfiguration interventions [3],[4].

Fault detection and isolation (FDI) based on analytical redundancy and observer techniques; parity space methods and process identification is currently a very active area with a significant progress in the last 20 years, [5], [6], and [7]. The purpose of automated diagnostic systems is the fast and accurate detection, isolation and identification of the causes of systems faults to allow the execution of appropriate actions (the repair or system reconfiguration) for the prevention of severe consequences.

As opposed to conventional techniques, where expensive equipment or accurate mathematical models are required, fuzzy logic and neural network technologies can be used to provide inexpensive but effective fault detection mechanism alternatives [8]. The general idea of application of fuzzy neural networks for instrumentation fault diagnosis was presented in [9], [10].

This study is dedicated to on-line diagnosis procedure based on fuzzy neural network for electrical drives [11]. The paper is organised as follows:

Section II describes the induction motor fault frame simulation, the residual generation and the justified reason for the choice of adopted technique. In Section III a general formulation of the problem is given. The general scheme of the detection and isolation based on an adaptive neuro-fuzzy structure is proposed. The instruments failures are detected and isolated by mean of an hierarchical neuro-fuzzy structure presented in Section IV and Section V. Experimental results are discussed in two stages according to the type of sensor malfunction to which correspond. Conclusions and perspectives are included in Section VI.

II. Three-phase induction motor problem statement

A. Motor description

A fast prototype simulation model of a three-phase induction motor is used to provide the experimental data under several reasonable assumptions. The modelling of induction motor in normal operating conditions has been achieved in the reference frame (dq) thanks to Park transformation in order to validate the control signal. Then we proceeded to model the faults (sensors and actuators) under steps and ramps-shaped. The experimental setup consists of a 15 kW, 260/380 V, 15/8.6 A, 4 pole, delta-connected squirrel-cage induction motor. A mechanical load was provided by a separately dc generator feeding a

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variable resistor. The simulation has been done with a frequency of 4kHz for each abnormal situation and the fault free one, on a period time of 8s.

B. Global residual generation

A three-phase induction motor simulation diagram, executed in Matlab/Simulink is used to extract the experimental data of motor behaviour under different operating conditions. The continuous model of a squirrel-cage induction motor is expressed in the reference frame fixed to the stator ($\alpha\beta$). A stator current signal contains potential fault information. The occurrence of the faults has been considered in steady state.

The most suitable measurements for diagnosing the faults under consideration, in term of easy accesibility, reliability, and sensitivity, are the stator currents (I_{sa}, I_{sb}) and speed sensor signal ω. Sensor faults ($f_I = [f_{Isa}\ f_{Isb}]^T$, f_ω) are modelled by additive inputs. The motor is driven by the well known vectorial algorithm control where the inverter is simplified (reduced) to a constant gain; this means that the stator voltages calculated by the control, V_{sa}, V_{sb}, V_{sc},

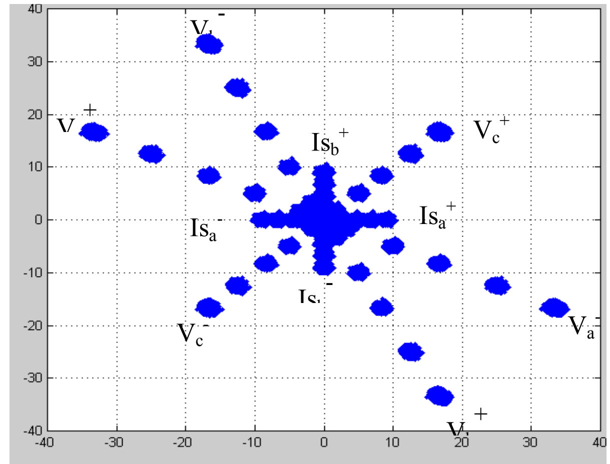

Fig. 1. The position of the residuals having fixed directions (r_isa, r_isb)

The figure 1 and figure 2 illustrating the fixed directional residuals and the moving residuals, suggest an intuitive solution consisting of a neuronal network that maps the whole residuals in two classes: the first class belongs to the those with fixed directions (FD) and the second

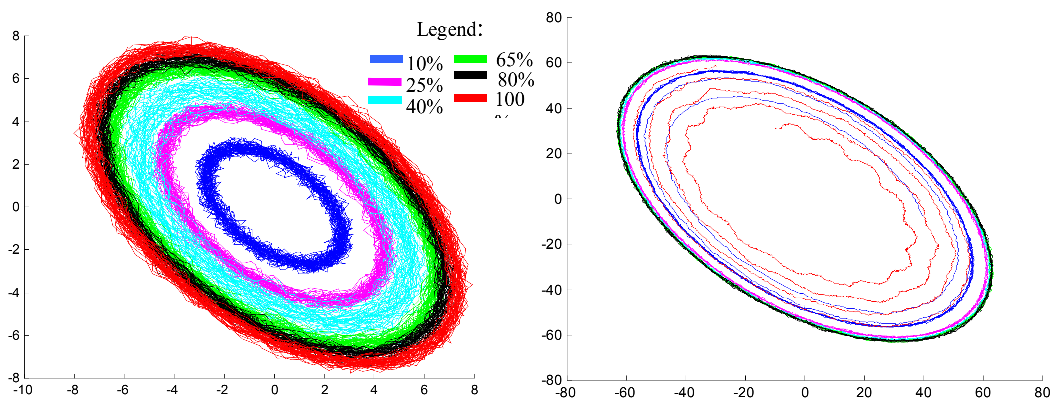

Fig.2 Time behaviour velocity sensor malfunction generated residuals displayed in (r_isa, r_isb) space for: a) positive faults, b) negative faults at nominal velocity of 1200RPM

are those actually applied to the induction motor, V_{sa}^{motor}, V_{sb}^{motor}, V_{sc}^{motor}. $f_v = [f_{Vsa}\ f_{Vsb}\ f_{Vsc}]^T$ represents the actuator faults. The residual generation has been studied in order to fulfil the following two requirements: the method does not depend on the type of control and, above all, the residuals have to be perfectly decupled from the load torque variations (as the load torque is a priori unknown). $r = [rI_{sa}\ rI_{sb}]^T$ represents the residuals consistent with the stator currents. The directional properties are studied in order to isolate the faults.

III. Fault Diagnosis Architecture

Our case study is limited to additive faults occurred in sensors and actuators and we don't pay attention to multiplicative (parametrical) faults. It was considered the hypothesis of simple faults (i.e. no simultaneous occurrence of independent faults).

corresponds to the faults speed, what mean moving direction (MD). The proposed structure (see figure 3) consists in two connected networks running in parallel. The networks are of ANFIS type, based on Ayoubi model network [12].

As it can be seen from figure 3 if the Output_1 indicates a fault speed then the outputs of the second network are neglected, otherwise, if the Output_1 indicates a directional fault then the Output_2 localises it.

The network structure is build in three steps:

Step1. The determination of fuzzy subsets for every input

variable. The initial values of the centres and variances characterising the membership functions of the first layer down, can be arbitrarily established (equidistant on the domain of definition of the linguistic variable) or applying a clustering algorithm of the type Fuzzy C-Means.

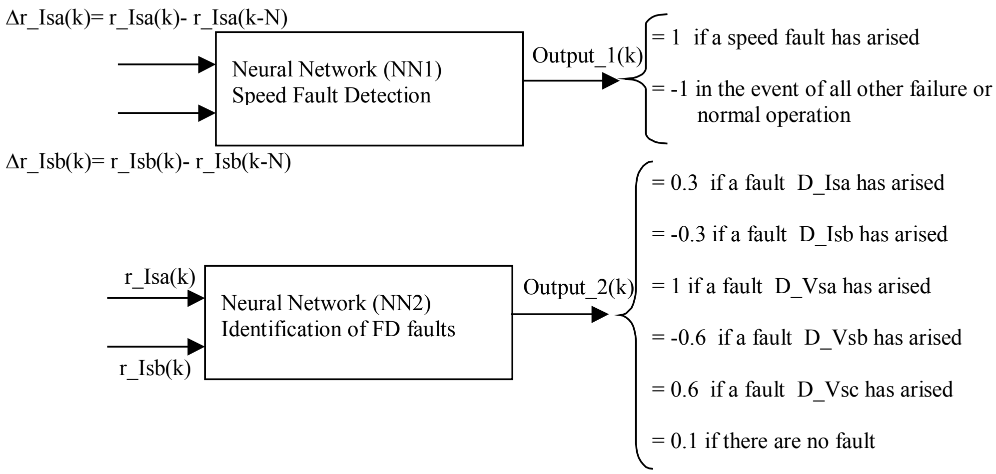

Fig.3 The neural proposed structure for instrumentation FDI

Step 2. Obtain the minimal dimension of the rule base. The extraction of most significant rule that determines the number of the nodes in the second layer.

Step 3. Optimisation of the parameters of rules determined at *Step 2*. The objective is to alterate the parameter values (c,w) of the network in order to improve the rule base minimising the quadratic criteria of performance,

$$J = \frac{1}{2}e^2 = \frac{1}{2}\left\{(f_d - f)^2\right\} \qquad (1)$$

where e means the prediction error defined as the difference between network output value and the target value. The optimised value of the generic parameter γ is calculated with the descendent method of gradient.

IV. Speed Sensor Fault Detection

The NN1 (see figure 4) receives at its inputs all residuals and generates two distinct decision signals: one for the FD residuals, and another for the MD residuals. Analysing the two figures, the differences between the behaviours of FD residuals and MD residuals respectively, are analytically transposed by:

$\Delta r\_isa|_{DF} \le \alpha_1 < \alpha_2 \le \Delta r\_isa|_{DV}$ and

$\Delta r\_isa = \Delta r\_isa(k) - \Delta r\_isa(k\text{-}N)$

$\Delta r\_isb|_{DF} \le \beta_1 < \beta_2 \le \Delta r\_isb|_{DV}$ and

$\Delta r\_isb = \Delta r\_isb(k) - \Delta r\_isb(k\text{-}N)$

where k is the present sampling step, k - N: the sampling step with N delay, N: the number of necessary step for the analysis, α_1, α_2: threshold for Δr_isa and β_1, β_2: threshold for Δr_isb.

In the choice of α_1, α_2, β_1, β_2, the analysis of FD residuals grouped into clusters is performed. The uncertainty is managed by two linguistic terms: ''Small' (S) and 'Large ' (L).

In the neuro-fuzzy structure the thresholds of fuzzification layer are constant with the value defined a priori. The choice of N is done in two steps:

i) The determination of the number of samples from a complete revolution in all three situations: ω_min, ω_nom, ω_max,

ii) The final value of N will be borne by a revolution at ω_max and such that r_isa, r_isb are enough large for a revolution at ω_min

To satisfy the on-line proprieties of FDI system and the high dynamic of system, it is required the smallest N value that verify the ii) constraint.

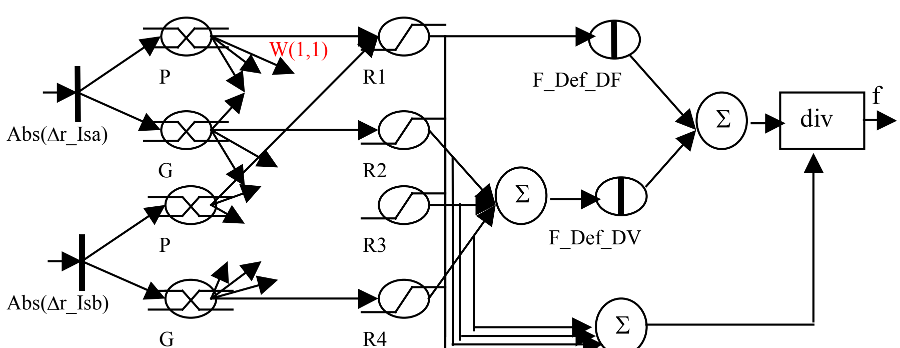

Fig.4 The neuro-fuzzy network architecture for speed sensor detection malfunctions

V. Fixed Oriented Faults Identification

Parameters in fuzzy systems have clear physical meaning so that rule-based and linguistic information can be incorporated into adaptive fuzzy system systematically. On the other hand, there are powerful algorithms to train various NN models to adapt difficult input-output mappings. The idea behind the fusion of these two technologies is to use the learning ability of NN's to implement and automate the fuzzy systems, which utilise the high-level human-like reasoning capability.

Starting from figure 2, a partition of the two dimensional residual space (r_isa, r_isb) is illustrated in Table I where it can be distinguished the spatial clustering of residuals.

procedure with the network convergence control at each new elimination of one rule. Consequently, starting with 32 rules, the present configuration counts 13 rules with the following distribution:

2 rules lead to "fault ∈D_Isa" decision 2 rules lead to "fault ∈D_Isb" decision

3 rules lead to "fault ∈D_Vsa" decision 3 rules lead to "fault ∈D_Vsb" decision

3 rules lead to "fault ∈D_Vsc" decision

Each node in the output layer represents one failure class. In the output layer singletons assigned to five faults considered have the values as figure bellow indicates.

TABLE I
THE LINGUISTIC PARTITION OF EXISTENCE DOMAIN OF FIXED ORIENTED RESIDUAL

r_Isa / **r_Isb**	NVL	NL	NM	NS	Z	PS	PM	PL	PVL
PVL		***D_Vsb***							
PL	*D_Vsa*		***D_Vsb***					*D_Vsc*	
PM		*D_Vsa*		*D_Vsb*	*D_Isb*		*D_Vsc*		
PS			*D_Vsa*	*D_Vsb* *D_Vsa*	*D_Isb*	*D_Vsc*			
Z			*D_Isa*	*D_Isa*		*D_Isa*	*D_Isa*		
NP				*D_Vsc*	*D_Isb*	*D_Vsa* *D_Vsb*	*D_Vsa*		
NM			*D_Vsc*		*D_Isb*	*D_Vsb*		*D_Vsa*	
NL		*D_Vsc*					*D_Vsb*		*D_Vsa*
NVL								*D_Vsb*	

A. Neuro-fuzzy architecture

The fault detector is a fuzzy inference system implemented on an adaptive network structure. Nine fuzzy sets are defined for each of the input variable. The neuro fuzzy adaptive inference system constructs automatically a mapping from the input space to the output space. Neuro-fuzzy structure and membership functions are constructed by observing the data set. The membership functions are parameterised with centre and width values.

The training procedure includes both unsupervised and supervised learning schemes. The unsupervised training provides a priori fuzzy partitioning of the input spaces by defining the initial membership functions and implementing the existence of the rules.

B. Extracted Knowledge

Once the form of the initial membership functions has been determined, fuzzy if-then rules can be derived. These rules permit a transfer of the knowledge from a numerical to a symbolic level where the fuzzy rules describe the fault in linguistic terms that can be interpreted by humans in an easier way.

At initial instant, the number of nodes of hidden layer is equal to the rules number. There are 4 rules for the decision D_Isa, 4 rules for the decision D_Isb and 8 rules for the decision of type D_Vx. The node number in the definitive topology (present) has resulted from 'trial and error'

For initialisation of pairs (c_i, σ_i) we have chosen the residuals domain $D_{r\_Isa}=[x\_min; x\_max]$ and $D_{r\_Isb}=[y\_min; y\_max]$ in order to generate the residuals on the range [-100; +100]% referred to the nominal measured value (current, voltage). The initialisation is based on an equidistant positioning for the c_i values on this interval and a properly choice for σ_i such that the entire domain is covered by the membership gaussian functions.

Simulated experimental results (see figure 5) are presented in terms of motor fault detection accuracy and knowledge extraction feasibility.

VI. CONCLUSION

This study demonstrates that the combination of neural networks with fuzzy systems can produce better diagnostic results, especially when there is an interest on the transparency in human understandable terms of neuro-fuzzy models. A compromise must be made between the interpretability and model precision. Fuzzy neural networks proposed approach allows fault isolation combined with delivering some additional information interpreted as fault certainty degrees. This takes advantage over FI methods basing on classical crisp logic. The experimental results suggest a promising future for using neural fuzzy inference systems for incipient fault detection in induction motors.

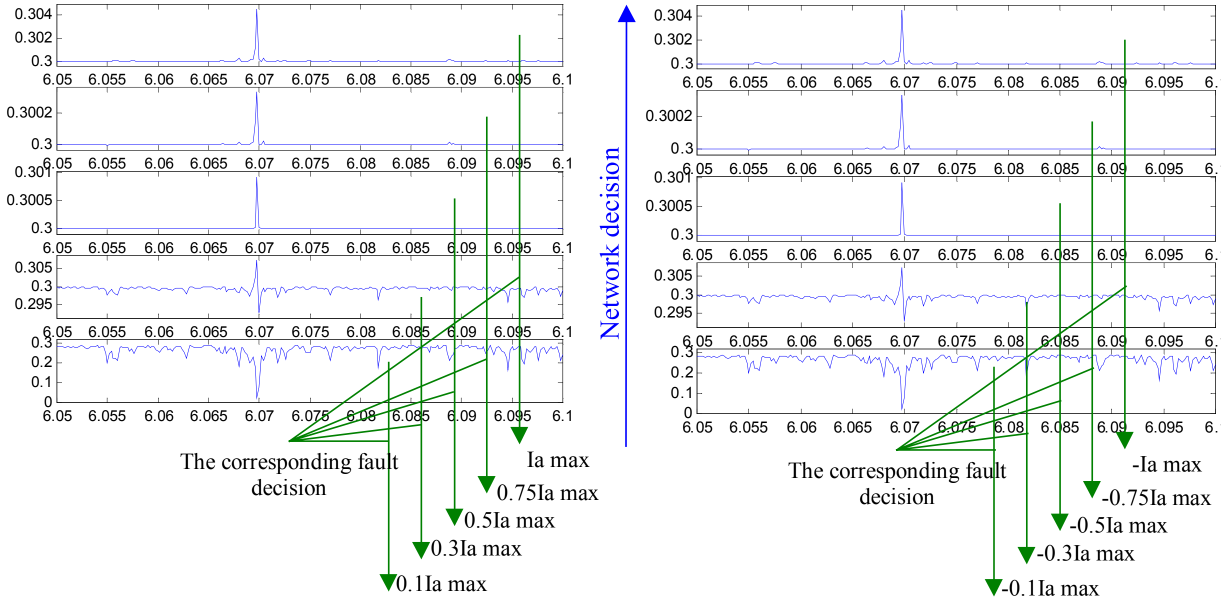

Fig.5 Step fault modelling a positive/negative bias of current sensor of phase A. Occurrence time in steady state is t = 6s. The crisp value corresponding to current sensor fault of phase A was established at 0.3.

some aspects which are currently under study are the application of developed technique to real process taking into account also the internal motor faults and the fundamental problem of robustness to parameter uncertainties and disturbances.

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