Robust Fault Diagnosis using a Data-based Approach and Structural Analysis

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Abstract: This paper presents a fault diagnosis approach that combines structural and data-driven techniques. The proposed method involves two phases. As a first step, the residuals structure is obtained from the structural model of the system by using structural analysis without considering mathematical models (only the component description of the system). Secondly, the analytical expressions for residuals are derived from available historical data using a robust identification approach. Through adaptive nets, residuals are adjusted by determining an interval model that takes into account the uncertainties and noises affecting the system. In the diagnosis part, residuals are tracked and evaluated. The presence of inconsistent residuals can be regarded as a fault, therefore thresholds for each residual are introduced. In addition to detecting faulty scenarios, it is also possible to determine which is the most likely fault that occurred in the system. To accomplish such classification, the proposed approach implements a Bayesian reasoning that uses the FSM (Fault Signature Matrix) that is obtained from the structural analysis of the system and residual activation signals. A brushless DC motor (BLDC) is used as a case study to illustrate the proposed approach. Simulation experiments illustrate the overall performance.

Keywords: Fault Diagnosis, Structural Analysis, ANFIS, Robust Identification, Bayesian Reasoning

1. INTRODUCTION

With the advent of the Industry 4.0 era, the research community has gradually realized the industrial interest in fault diagnosis. Currently, the majority of the existing model-based approaches require the system mathematical model including both equations and parameters. Nevertheless, in real industrial systems it is very difficult or time consuming to obtain a mathematical model of the system that describes precisely its behavior, and even harder, to obtain the model uncertainty required for including robustness in the fault diagnosis process. Thereby, a method that only requires the knowledge of the structural model can be useful to overcome such difficulties. Once the structure of the resulting analytical redundancy relations have been obtained, they can be identified from historical data of normal operation using machine learning and robust identification, determining the model from data altogether with its uncertainty bounds.

In this paper, a robust fault diagnosis approach that combines the structural analysis and data-driven techniques extending the applicability of conventional model-based diagnosis methods is proposed. Some researchers have already explored similar ideas, for instance, using techniques like Grey-box recurrent neural networks to generate residuals in order to develop a hybrid fault diagnosis method [4][5]. Another outstanding research is about combining the state space neural networks and model-decomposition methods for fault diagnosis [1]. Nevertheless, these researches do not consider robustness in fault diagnosis. On the other hand, most of the existing approaches are based on application dependent methods that extract features of the measured variables. In this work, we will avoid the need to have the mathematical model of the system by obtaining the mathematical expressions of the residuals from data using an Adaptive Neuro-Fuzzy Inference System approach, ANFIS [7], and considering parameter uncertainty using interval methods. Many steps of this approach can be dealt with alternative methods. For example, there exist various methods to generate residuals from the structural model of the system. In the same way, the identification of the residuals can also be done with other machine learning methods different from the one proposed in this paper. For academic purposes, the overall procedure will be applied to a brushless DC motor (BLDC), even it can be understood as a general procedure to model structural relations.

The structure of the paper is the following: Section 2 introduces the proposed approach and the considered case study. Sections 3 and 4 present a procedure for obtaining the MSO model from data based on the ANFIS algorithm. Section 5 presents the bounding of the MSO model uncertainty. Section 6 presents the fault isolation procedure based on Bayesian reasoning. Section 7 illustrates the results for the considered case study (a BLDC motor). Section 8 draws the conclusions of the paper.

2. PROPOSED APPROACH

2.1 Description

The proposed method is targeted to study systems where the exact analytic mathematical expressions of a model are too difficult or time consuming to be obtained. Instead of an exact mathematical model, it is assumed that only a structural model description and a set of output observed variables, y, as well as the set of system inputs, u, are available.

Thinking of this general case where only structural relations can be defined, the use of adaptive networks allows to model the relations between variables linked in a residual (Sections 3 and 4). Due to modelling errors and signal noise, trained residuals can present values different from zero while processing non faulty data. This fact leads to a secondary signal processing to accomplish residual activation reasoning. Looking for robustness, the proposed approach adapts interval techniques on a regressor description of ANFIS net (Section 5). To overcome the issues associated to oscillatory or asynchronous residual activation between different signals, a probabilistic fault isolation approach based on Bayesian reasoning has been developed (Section 6).

2.2 Running example

The proposed methodology is illustrated in this paper using a brushless DC (BLDC) motor case study (see [6] for a detailed description of the model). The simplified dynamic model used to simulate the data can be described as follows:

$$\textbf{e1: } V(t) = (L_{eq}+f_{L_1})\,\frac{dI}{dt}+(R_{eq}+f_{L_2})\,I(t)+K_e\,\omega(t) \quad (1)$$

$$\textbf{e2: } T_L(t) = -J\,\frac{d\omega}{dt} - B_r\,\omega(t) + K_T\,I(t) \quad (2)$$

$$\textbf{e3: } y_1 = I(t) + f_i \quad (3)$$

$$\textbf{e4: } y_2 = \omega(t) + f_w \quad (4)$$

In addition to the variables and parameters describing the motor, this case study also analyzes several faults. For illustration purposes, three different faults are examined, where f_i and f_w are additive faults associated with intensity and angular speed measurement respectively, and f_{L_i} is a parametric fault affecting the nominal value of the induction coil. The latter is presented as two variables in equation (1) (f_{L_1} affecting inductance and f_{L_2} the resistance), both consequences of the coil defect, but for practical purposes will be referred to as one variable, f_L.

3. OBTAINING MSO STRUCTURE WITHOUT MODEL EQUATIONS

3.1 Procedure

The proposed approach exploits the advantage of structural analysis. This procedure is commonly used while considering analytical defined models, but it can also be generalized to treat ill-defined ones, defined by a structural description. Let assume that equations (1) to (4) (indeed only needed for data generation purposes) are unknown and only its structure is available, described by

$$\textbf{E1: } [V, I, dI, \omega, f_L] \quad (5)$$

$$\textbf{E2: } [T_L, \omega, d\omega, I] \quad (6)$$

$$\textbf{E3: } [y_1, I, f_i] \quad (7)$$

$$\textbf{E4: } [y_2, \omega, f_\omega] \quad (8)$$

Since the BLDC is a dynamic system, it is necessary to include two more restrictions to represent the differential relations between variables in order to accomplish a proper variable matching. In this case, the angular velocity and intensity derivatives over time are considered as special restrictions, $E5$ and $E6$, including the differential dependency trough a reserved variable: $\boldsymbol{dif}$.

$$\textbf{E5: } [I, dI, dif] \quad (9)$$

$$\textbf{E6: } [\omega, d\omega, dif] \quad (10)$$

It can be assumed that V and T_L are known variables along with the sensors measures y_1 and y_2. In Table 1 the different elements used in the Structural Analysis are presented as known variables (**Z**), unknown variables (**X**), restrictions defined by the model (**E**) and faults to be diagnosed (**F**).

Table 1. *BLDC* structure

Category	Variables
Z	y_1 y_2 V T_L
X	I ω dI $d\omega$
E	$E1$ $E2$ $E3$ $E4$ $E5$ $E6$
F	f_i f_ω f_L

Structural Analysis aims to find computable overdetermined subsets of equations for a given structural model. These subsets allow to compute estimations that rely on the system being healthy and use the remaining variables (given by the overderminded nature of the subset) to contrast with the real behaviour of the system. These feasible overdetermined subsets of degree 1 are called Minimally Structurally Overdetermined sets (MSO).

These subsets (MSO) are obtained by means of algebra of sets from the model canonical decomposition. Even tough different approaches and algorithms exist to define them, the proposed method applies the techniques contained in *Fault Diagnosis Toolbox* [8]. This methodology provides deep interpretability, allowing to infer the causal relationship between the equations used in each subset during residual computation. The chosen MSO sets for this case study are presented in Table 2.

Table 2. MSO set of BLDC model

MSO	E1	E2	E3	E4	E5	E6
MSO_1	-	*der*	*der*	*int*	-	*int*
MSO_2	*der*	-	*int*	*der*	*int*	-
MSO_3	*der*	*mixed*	-	*int*	*mixed*	*int*

For each MSO, computational causality will depend on the chosen residual equation, where *int* denotes integral causality, *der* derivative causality, *algebraic* algebraic causality and *mixed* mixed causality. Equations marked with - are non participants of the MSO defined by that specific row.

Given the MSO sets described in Table 2, we can identify which are the equations used in each subset. If an MSO is used to generate a residual (see Section 3.2), any discrepancy between measures and estimations must be due to one (or more) of the equations it contains. However, the elements in the equations are either known or estimated, therefore the observed deviations must be due to changes in these known parameters. The role of the faults presented in equations (1) to (4) is to account for these deviations from the healthy behaviour.

As a result, we can link each MSO to the faults that could be responsible for the ill estimations generated. The Fault Signature Matrix (FSM) for the considered BLDC motor is presented in Table 3, allowing to infer the underlying fault from the observed residual activation.

Table 3. Fault sensitivity

	$\mathbf{MSO_1}$	$\mathbf{MSO_2}$	$\mathbf{MSO_3}$
$\mathbf{f_i}$	1	1	0
$\mathbf{f_\omega}$	1	1	1
$\mathbf{f_L}$	0	1	1

3.2 MSO structure

From the model structure it is possible to draw the computational graph described by the causal relationships between the equations in an MSO. An example obtained for the MSO_3 and derivative causality is presented.

$$\begin{aligned}
&E4 : \omega(k) = y_2(k) \\
&E6 : d\omega(k) = \frac{\omega(k) - \omega(k-1)}{T_S} \\
&E2 : i(k) = \xi_1(\omega(k), d\omega(k), T_L(k)) \\
&E5 : di(k) = \frac{i(k) - i(k-1)}{T_S} \\
&E1 : \textbf{Residual} = V(k) - \xi_2(i(k), di(k), \omega(k))
\end{aligned} \tag{11}$$

In the computational sequence example presented in (11), ξ_1 and ξ_2 are unknown functions. The proposed solution consists in generating an estimator for the target variable $\hat{V}(k)$ (given only known variables in the MSO) to be compared with the real values $V(k)$. In (12), we can observe how this consideration leads to a definition of a residual.

$$\begin{aligned}
&\hat{V}(k) = \xi(T_L(k), T_L(k-1), y_2(k), y_2(k-1)) \\
&\textbf{Residual} = V(k) - \hat{V}(k)
\end{aligned} \tag{12}$$

In the example of MSO_3 while considering derivative causality, the supply voltage is estimated ($\hat{V}$) from previous and present measurements, by means of an adaptive net ξ. Using structural analysis, we can identify the elements required to compute the voltage in the absence of uncertainties in the physical model.

The discrepancies between the measured voltage and the estimated one must come from changes in the underlying system. In the case of the equations (1) to (4), these changes are fully accounted by the fault variables that in a healthy behaviour are equal to 0. Therefore, the deviations between the simulated model and the real one must come from values of f_i, f_w or f_L different from 0.

For a higher degree of fault isolation, the same computational analysis applied to MSO_3 and the sequence (11) can be extended to all the considered MSO sets. Table 4 summarizes the obtained results for this case study.

Table 4. I/O Network Structure

MSO	Inputs(k)	Inputs(k-1)	Reference(k)
MSO_1	y_2 , T_L	y_2	y_1
MSO_2	y_1 , V	y_1	y_2
MSO_3	y_2 , T_L	y_2 , T_L	V

4. RESIDUAL MATHEMATICAL EXPRESSIONS FROM DATA USING ANFIS

Let consider a particular MSO that involves a set of variables according to the structural analysis result presented in previous section. Then, let consider that one of the variables is the output and the rest of variables are related by an unknown mathematical expression g as follows

$$y(k) = g(\varphi(k)) \tag{13}$$

where $\varphi(k)$ is the list of remaining variables (regressor) of the associated MSO.

In this paper, to obtain the MSO mathematical expressions from data, ANFIS neural networks (NN) will be used. ANFIS NN returns a Takagi-Sugeno model for each MSO using only the regressor structure obtained in (5) to (10) for the BDLC motor using the approach proposed in [7]. ANFIS consists of five layers. The first layer is in charge of the fuzzyfication through a membership function. The second layer deals with the rules by using the fuzzyfied values obtained in the first layer. The third layer is the normalization layer where the strength of each rule is calculated. The fourth layer is the defuzzyfication layer where the different rules are combined to produce a value. Finally, the fifth layer is in charge of summing the outputs obtained by each layer

$$y(k) = \sum_{i=1}^{n_r} \overline{\omega}_i(p_k) g_i(k) = \frac{\sum_{i=1}^{n_r} \omega_i(p_k) g_i(k)}{\sum_{i=1}^{n_r} \omega_i(p_k)} \tag{14}$$

where n_r is the number of rules (subsystems), $\omega_i(p_k)$ is a specific scalar rule weight, p_k represents the operating point and the local model g_i can be expressed in regressor form as follows

$$g_i(k) = \varphi_i(k)\theta_i \tag{15}$$

This allows writing the ANFIS model in regressor form

$$\hat{y}(k) = \varphi(k)\theta^0(p_k) \tag{16}$$

where

$$\varphi(k) = (\varphi_1(k), ..., \varphi_i(k), ..., \varphi_{n_r}(k)) \tag{17}$$

$$\theta^0(p_k) = \begin{pmatrix} \overline{\omega}_1(p_k)\theta_1 \\ ... \\ \overline{\omega}_{n_r}(p_k)\theta_{n_r} \end{pmatrix} \quad (18)$$

Let consider an overall of $[x_1, ..., x_{n_i}]$ inputs. Since consequent systems $\theta_i, i \in [1, ..., n_r]$ are defined as general linear systems with an independent term, the proposed formulation defines each subsystem regressor as

$$\varphi_i(k) = (x_1, x_2, ..., x_{n_i}, 1) \quad (19)$$

Under this consideration, the new parameter space $\theta^0(p_k)$ has an overall of $n_\theta = n_r(n_i + 1)$ varying parameters that depend on the operating point.

5. BOUNDING UNCERTAINTY

Using the regressor formulation for the ANFIS model obtained above, the goal of this section is to provide a method to estimate the parametric uncertainty and determine the output prediction bounds, adapting the procedures described for LPV systems in [2][3]. The exposed procedure must be carried on once the parameter training has concluded. The parameter uncertainty estimation λ will be saved and used during the diagnosis stage. Considering that the ANFIS model (16) is affected by additive bounded noise $|e(k)| < \sigma$

$$\hat{y}(k) = \varphi(k)\theta(p_k) + e(k) \quad (20)$$

The goal is to find the parametric uncertainty $\lambda(k) = (\lambda_1(k), ..., \lambda_m(k), ..., \lambda_{n_\theta}(k))^T$ such that for the training data set containing N input/output pairs allows to bound $y(k)$ as

$$y(k) \in \left[\underline{\hat{y}}(k) - \sigma, \overline{\hat{y}}(k) + \sigma\right] \ \forall k \in \{1, \cdots, N\} \quad (21)$$

Considering the following parametrisation

$$\theta(p_k) \in [\theta^0(p_k) - \lambda(k), \theta^0(p_k) + \lambda(k)] \quad (22)$$

where $\theta^0(p_k)$ are the nominal ANFIS parameters. Extending (17) as $\varphi(k) = (\alpha_1(k), ..., \alpha_m(k), ..., \alpha_{n_\theta}(k))$, condition (21) can be rewritten as follows

$$\hat{y}^0(k) - \sum_{m=1}^{n_\theta} \lambda_m |\alpha_m| - \sigma \leq y(k) \leq \hat{y}^0(k) + \sum_{m=1}^{n_\theta} \lambda_m |\alpha_m| + \sigma \quad (23)$$

where $\hat{y}^0(k) = \varphi(k)\theta^0(p_k)$ is the nominal ANFIS estimation. Considering $\lambda_m = \lambda\, \lambda_m^0(k) = \frac{\lambda}{|\alpha_m(k)|}$ and n_θ as the overall number of variant parameters, (23) leads to the following two conditions

$$\lambda \geq \frac{y(k) - \hat{y}^0(k) - \sigma}{n_\theta} \quad , \quad \lambda \geq \frac{\hat{y}^0(k) - y(k) - \sigma}{n_\theta} \quad (24)$$

Then, the satisfaction of (21) is achieved by selecting

$$\lambda = \sup_{k \in [1, ..., N]} \left(\max\left(\frac{|y(k) - \hat{y}^0(k)| - \sigma}{n_\theta}, 0 \right) \right) \quad (25)$$

Thus, output prediction interval $\left[\underline{\hat{y}}(k), \overline{\hat{y}}(k)\right]$ can be evaluated considering parametric uncertainty as follows:

$$\overline{\hat{y}}(k) = \hat{y}^0(k) + \sum_{m=1}^{n_\theta} \lambda_m(k) |\alpha_m(k)| \quad (26)$$

$$\underline{\hat{y}}(k) = \hat{y}^0(k) - \sum_{m=1}^{n_\theta} \lambda_m(k) |\alpha_m(k)| \quad (27)$$

6. FAULT DIAGNOSIS USING A BAYESIAN APPROACH

6.1 Residual evaluation

For each MSO_j of the considered set of MSO, residual signal can be computed as the difference between the known and estimated variable

$$r_j(k) = y_j(k) - \hat{y}_j(k) \quad (28)$$

Each residual signal is affected by measurement noise and uncertainty due to parameter estimation. This fact implies the need of some robust residual evaluation to determine whether the signal is consistent or not. The proposed approach uses the prediction interval $\left[\underline{\hat{y}}_j(k), \overline{\hat{y}}_j(k)\right]$ to establish an adaptive residual interval $[\underline{r}_j(k), \overline{r}_j(k)]$ as follows

$$\overline{r}_j(k) = \overline{\hat{y}}_j(k) - \hat{y}_j(k) \quad (29)$$

$$\underline{r}_j(k) = \underline{\hat{y}}_j(k) - \hat{y}_j(k) \quad (30)$$

Now, a new test condition for residual activation can be formulated as

$$r_j(k) \in [\underline{r}_j(k), \overline{r}_j(k)] \quad (31)$$

Since residual boundaries are known, it is possible to normalize each residual signal by means of Kramer function

$$\phi_j(k) = \begin{cases} \dfrac{(r_j(k)/\overline{r}_j(k))^4}{1 + (r_j(k)/\overline{r}_j(k))^4}, & \text{if } r_j(k) \geq 0 \\ -\dfrac{(r_j(k)/\underline{r}_j(k))^4}{1 + (r_j(k)/\underline{r}_j(k))^4}, & \text{if } r_j(k) < 0 \end{cases} \quad (32)$$

where $\phi_j(k) \in [-1, 1]$ can be used to determine the degree of inconsistency. Considering the results of the residual evaluation, the test condition (31) can be computed as follows

$$\Phi_j(k) = \begin{cases} 1, & \text{if } \phi_i(k) \geq 0.5 \\ 0, & \text{if } \phi_i(k) < 0.5 \end{cases} \quad (33)$$

Assuming an overall set of m MSO, the previous residual evaluation process will generate a consistency signal vector

$$\phi(k) = (\phi_1(k), ..., \phi_j(k), ..., \phi_m(k)) \quad (34)$$

and a residual activation signal

$$\Phi(k) = (\Phi_1(k), ..., \Phi_j(k), ..., \Phi_m(k)) \quad (35)$$

that will be used during the fault isolation process.

6.2 Bayesian reasoning

Let consider a generic FSM for a set of residuals derived from m MSO and n_f faults, presented in Table 5.

Table 5. Generic FSM

Residual	f_1	...	f_l	...	f_{n_f}
r_1	0	...	1	...	1
...	...	...	...	...	...
r_m	1	...	0	...	1

Each column of the matrix contains a specific fault signature, denoted from now on as FSC_l. For each considered fault, the Bayesian probability distribution can be computed at every time instant as follows

$$p(f_l|\Phi) = \frac{p(\Phi|f_l)\ p(f_l)}{\sum_{k=1}^{n_l} p(\Phi|f_k)\, p(f_k)} \tag{36}$$

where $p(f_l)$ is the prior probability of f_l, Φ is the residual activation signal and $p(\phi|f_l)$ is the actual degree of occurrence, estimated as

$$p(\Phi|f_l) = |\phi(k)|\ \frac{FSC_l}{n_l} \tag{37}$$

where $n_l = \sum FSC_l$ and $\phi(k)$ is the residual consistency signal. The proposed methodology assumes that the initial fault probability distribution is equiprobable among all considered faults. Once a residual activation is detected, the prior probability distribution can be updated on each iteration, redefining the prior probability as follows

$$p(f_l)(k+1) = p(f_l|\Phi)(k) \tag{38}$$

The overall implemented procedure flowchart is summarized in Figure 1.

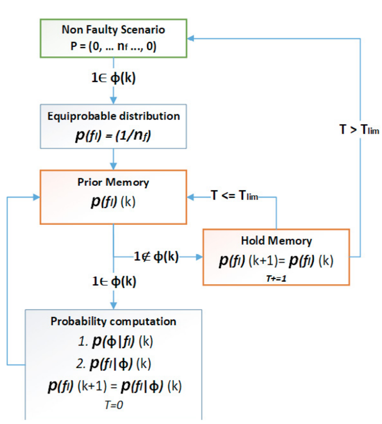

Fig. 1. Implemented Bayesian reasoning flowchart

In the classic isolation approach, the iterative process will end up when all residuals become deactivated, that is $\sum \Phi(k) = 0$. Residual activation signals can present oscillatory behaviour for a given fault scenario, while facing noisy signals, and considering the existence of modelling errors. This will lead to a continuous break in the iterative loop, losing the probabilistic context for imminent residual activation signals. To attenuate this effect, a second probabilistic state memory, *hold memory* has been considered. In case of facing a complete residual deactivation, last probability estimation will be stored during T_{lim} time instants before assuming non faulty behaviour.

7. RESULTS

In this section, we demonstrate the overall procedure by using the running example that is presented along the paper. All involved data, including measurement noise in both output and control signals, was simulated. The considered MSO sets, presented in Table 2, are modeled using the ANFIS approach (Section 4) through an adaptation of the hybrid training method described in [7]. In order to simulate an inductance failure scenario, the same simulation conditions were carried out, but with a 10% deviation in nominal inductance values. Following the MSO_3 example, a general overview of trained residual performance over test and faulty data is shown in Figure 2.

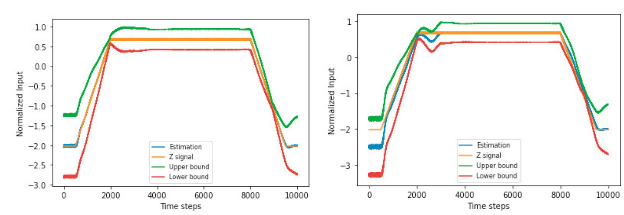

Fig. 2. ANFIS modelling: Trained MSO_3 response

In non-faulty conditions (left), both estimation and known signal (*Z signal*) are contained within the uncertainty boundaries, displaying few significant discrepancies. In the case of faulty data (right), the objective variable (*Z signal*) associated to MSO_3 crosses the residual uncertainty boundaries, as expected, since MSO_3 is affected by f_L. This will result in a specific residual activation signal, in this case $\Phi_3(k)$.

According to the diagnosis procedure detailed in Section 6.2, residual activation signals $\Phi_1(k)$, $\Phi_2(k)$, and $\Phi_3(k)$ derived from the trained model can be used to identify the most probable fault causing the residual activation. The isolation results obtained while processing faulty data are presented in Figure 3.

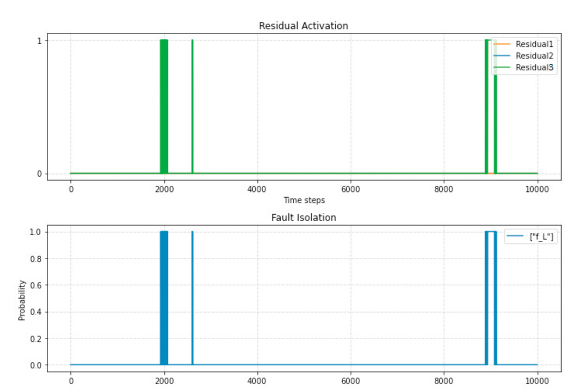

Fig. 3. Residual activation and fault isolation. $T_{lim} = 10$

The fault isolation results presented in Figure 3 shows that f_L is the most probable fault, being consistent with the considered faulty scenario. Residual signals tend to present boundary crossing during transitory dynamics, in this case forced by the acceleration and deceleration of the BLDC caused by the trapezoidal control signal. These regions present high intensity derivatives, amplifying the inductance effects on the model's estimation.

Once the general isolation has been presented, it is time to increase the resolution in order to see how the Bayesian fault probability is determined over time. An extract of the fault isolation procedure for the classic and the proposed Bayesian approach is presented in Figure 4.

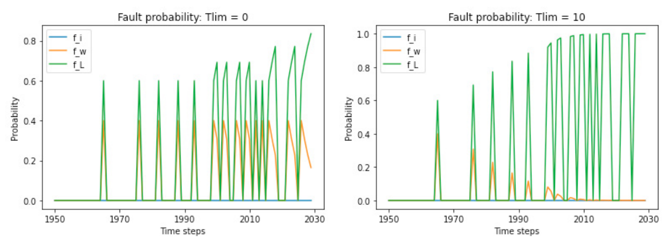

Fig. 4. Extract of fault probability distribution

For a clearer interpretation, model FSM is presented again before proceeding with the explanation.

	$\mathbf{MSO_1}$	$\mathbf{MSO_2}$	$\mathbf{MSO_3}$
$\mathbf{f_i}$	1	1	0
$\mathbf{f_\omega}$	1	1	1
$\mathbf{f_L}$	0	1	1

Since MSO_3 activation is not compatible with f_i signature, this fault will not cause any confusion during fault isolation. On the other hand, f_w depends on all residuals, while f_L only depends on MSO_2 and MSO_3 activation. Since MSO_1 does not present any inconsistency, both approaches end up by classifying the underlying fault f_L as the most probable. However, the continuous oscillation in residual activation signals plays a negative role in terms of isolation convergence while considering the classic approach ($T_{lim} = 0$). As shown in the left image, the loss of probabilistic context after each residual deactivation considers upcoming residual activation as independent. To overcome this issue, the same faulty data has been processed, but this time, considering a hold interval of $T_{lim} = 10$. Under this consideration, fault probabilistic context is stored up to 10 time instants after a complete residual deactivation. As it can be seen on the right image, the probability associated to f_w decreases as new residual activation signals are considered, obtaining a complete isolation (probability of 1.0 or a 100%) of the underlying inductance fault.

8. CONCLUSIONS

This paper has presented a robust fault diagnosis approach that does not require the exact mathematical model of the system. The proposed method uses structural analysis to determine the residual structure. Since only the model structure is needed, it is possible to treat complex industrial systems, without requiring precise mathematical models. The MSO generation can be easily automated, allowing to define a generic method to analyse a huge variety of real industrial systems. Even tough an MSO structure is known, its computational graph can not be directly matched since the analytical model is unknown. Since residual estimators only depend on known data, the analytical expressions of residuals can be estimated from available historical data, in this case by means of machine learning approaches. The proposed approach uses ANFIS neural net since it can be formulated in a regressor form. Taking profit of this fact, a robust parameter identification approach for ANFIS based on parameter uncertainty is proposed. The obtained MSO uncertainty bounding can be used to detect residual activation in a robust manner. Throughout a Bayesian reasoning, residual activation signals can be interpreted and transformed into fault probability. The recursive computation of the method attenuates the effects caused by non synchronized residual activation while classifying the most probable fault. As an improvement, a second memory source has been considered to attenuate the effect of oscillatory residual activation caused by noise and modelling errors. During the whole paper, the approach has been illustrated with a BLDC system. Currently, this approach is being applied to a real complex cooling system in collaboration with an industrial partner.

ACKNOWLEDGEMENTS

This work has been co-financed by the Spanish State Research Agency (AEI) and the European Regional Development Fund (ERFD) through the project SaCoAV (ref. MINECO PID2020-114244RB-I00), by the European Regional Development Fund of the European Union in the framework of the ERDF Operational Program of Catalonia 2014-2020 (ref. 001-P-001643 Looming Factory) and by the DGR of Generalitat de Catalunya (SAC group ref. 2017/SGR/482).

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