Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 54-7 (2021) 61–66

Modulation-Function-Based Finite-Horizon Sensor Fault Detection for Salient-Pole PMSM using Parity-Space Residuals

Benjamin Jahn * **Yuri A.W. Shardt** *

* *Department of Automation Engineering, Technical University of Ilmenau, D-98684 Ilmenau, Germany*

Abstract: An online model-based fault detection and isolation method for salient-pole permanent magnet synchronous motors over a finite horizon is proposed. The proposed approach combines parity-space-based residual generation and modulation-function-based filtering. Given the polynomial model equations, the unknown variables (*i.e.* the states, unmeasured inputs) are eliminated resulting in analytic redundancy relations used for residual generation. Furthermore, in order to avoid needing the derivatives of measured signals required by such analytic redundancy relations, a modulation-function-based evaluation is proposed. This results in a finite-horizon filtered version of the original residual. The fault detection and isolation method is demonstrated using simulation of various fault scenarios for a speed controlled salient motor showing the effectiveness of the presented approach.

Keywords: Permanent Magnet Synchronous Motor, Sensor Fault Detection, Analytic Redundancy Relations, Modulation Functions

1. INTRODUCTION

Since permanent magnet synchronous motors (PMSM) are very efficient and have high power density, they are frequently used in various industrial fields. In many cases, the detection of sensor errors affecting current or speed / position measurements can improve the safety and minimize environmental impact and economic losses. Online fault detection and isolation (FDI) allows a process to be monitored, unusual behavior to be identified, and appropriate countermeasures to be taken.

In the last few decades, much research has been performed in FDI for both linear and nonlinear systems, resulting in many different types of methods that can be classified into two main categories: data-driven FDI and model-based FDI (Chen et al., 2001; Ding, 2008). Unlike model-based FDI, data-driven FDI does not require accurate *a priori* models but uses the available historical data, which makes them more suitable for large-scale systems. Data-driven approaches include many different methods including multivariate statistics and machine learning (Qin, 2012; Chen et al., 2016, 2017; Hua et al., 2018).

Of the model-based FDI methods, the explicit parity-space-based approach is the most common and uses a set of analytic redundancy relations (ARR) derived from the model equations that involve only known quantities and can be used for residual generation (Isidori et al., 2001; Blanke et al., 2015). The parity-space approach was first considered for linear systems by Chow and Willsky (1984) and was then generalized to cover polynomial systems (Frank, 1990; Kinnaert, 2003). Various different methods have been developed to eliminate the unknown quantities, including *e.g.* Buchberger's algorithm (Buchberger, 1985), *p*-adic/modular methods (Arnold, 2003), or Ritt's algorithm (Ritt, 1950).

Despite originating from a model-based perspective, in (Ding, 2014) a data-driven method is proposed to identify parity vectors directly from historical data independent of explicit *a priori* model information. Recent research shows how to find the optimal data-driven parity vector by means of an iterative approach (Jiang et al., 2021).

In general, the evaluation of model-based residuals requires the derivatives of measured input and output quantities. In Jahn et al. (2020), three analytic redundancy relations (ARR) for sensor fault detection of a salient-pole permanent magnet synchronous motor are presented. In order to obtain estimates of the required derivatives of the measured input and output quantities as needed by the proposed ARR, robust exact differentiators were used. To guarantee finite-time exact convergence in the absence of noise, the gains of the robust exact differentiators need to be chosen with respect to the Lipschitz constant of the highest order derivative needed, as shown by Levant (2003). In applications requiring a wide range of operation, it may be necessary for this constant to be very large resulting in high observer gains. In the presence of considerable measurement noise, such high gains amplify the noise's influence on the residuals rendering the decision making challenging or even unfeasible. Thus, this paper proposes a modulation-function-based approach to residual generation resulting in a residual signal evaluated over a finite horizon for sensor fault detection. The proposed method is tested on a simulated speed-controlled motor.

After this introduction, Section 2 examines model-based FDI and parity-space-based residual generation for polynomial systems, as well as examining modulation functions

10.1016/j.ifacol.2021.08.335

and how they can be used to avoid needing derivatives of measured signals. Section 3 proposes the finite-horizon residual generation using modulating functions. In Section 4, the background regarding the model of the permanent-magnet synchronous motor is presented. Finally, Section 5 validates the proposed finite-horizon sensor fault detection using a simulated PMSM system.

2. BACKGROUND

The basic idea in model-based FDI is to compare, using a model, the expected system behavior against the observed system behavior. Residual signals are used to quantify the amount of mismatch or discrepancy between the two systems. Figure 1 shows the quantitative model-based FDI approach that has two stages: a diagnostic / residual signal generation stage and a decision making or diagnostic classification stage (Chen et al., 2001). A residual signal must satisfy the specific properties given by Definition 1. This means that the generation or construction of a residual signal is a nontrivial task especially for nonlinear systems. The different residual generation approaches can be divided into three categories: observer-based, parity-space-based and parameter-estimation-based / parameter-identification-based approaches (Frank, 1990).

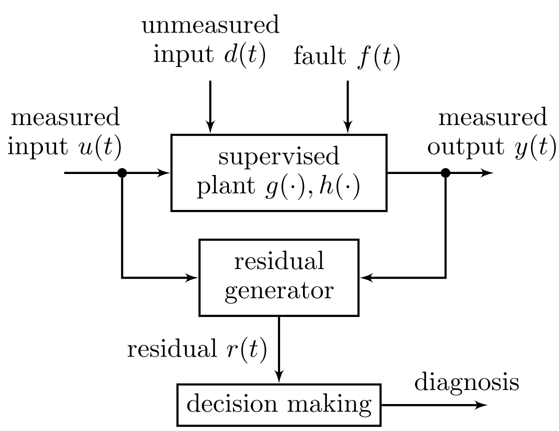

Fig. 1. The two stages in quantitative model-based FDI (Jahn et al., 2020)

Definition 1 (Jahn et al., 2020)**.** *A residual is a signal that is zero when the system under diagnosis is free of faults, and nonzero when particular faults are present in the system. Additionally, a residual must be invariant to any unmeasured and therefore unknown input signals (e.g. disturbances) as their influence is not considered to be a fault.*

2.1 Parity-Space-Based Approach for Polynomial Nonlinear Systems

Chow and Willsky (1984) were the first to consider the parity-space approach for linear systems. Later, it was generalized to cover polynomial systems (Kinnaert, 2003; Isidori et al., 2001). The approach is based on analytic redundancy relations (ARR) that can be used for residual generation and subsequent FDI (Chen et al., 2001).

Consider the class of polynomial multi-input, multi-output (MIMO) systems

$$\dot{x} = g(x, u, d, f) \quad (1a)$$
$$y = h(x, u, d, f) \quad (1b)$$

where $g : \mathbb{R}^n \times \mathbb{R}^p \times \mathbb{R}^{n_d} \times \mathbb{R}^{n_f} \to \mathbb{R}^n$ and $h : \mathbb{R}^n \times \mathbb{R}^p \times \mathbb{R}^{n_d} \times \mathbb{R}^{n_f} \to \mathbb{R}^q$ are polynomial functions of their arguments, *i.e.* x is the state vector, u the vector of known inputs, d the vector of unknown inputs or disturbances, and f the vector of faults.

The following description summarizes the steps presented in Kinnaert (2003), where further details can be found. Based on the successive time derivatives of the outputs y, and the subsequent elimination of the states x and the unmeasured input d, a set of polynomials (resulting ARR) is derived

$$P(Y, U, F) = P_r(Y, U) + P_f(Y, U, F) = 0 \quad (2)$$

which depends on the outputs and their derivatives Y, the inputs and their derivatives U, and the faults and their derivatives F.[1] These ARR can be further decomposed into fault-dependent polynomials P_f and fault-independent polynomials P_r. As P_r must equal to zero in faultless operation, it can be used as a parity /residual signal for fault detection

$$r(t) = P_r(Y(t), U(t)) \quad (3)$$

However, the fact that these expressions consist of the derivatives of the measured input and output constitutes the main drawback of this method for residual generation. As it is often the case in practice, these derivatives are not accessible using numerical differentiation due to measurement noise. This problem becomes worse as the order of derivatives needed increases. Most often, it is proposed to use linearly filtered input and output signals making their filtered derivatives accessible. However, in case of polynomial residuals, the evaluation based on these filtered quantities does not result in a similarly filtered residual signal as for linear system residuals. Here a finite-horizon filtering method based on modulation functions is used in order to deal with the noise.

2.2 Modulation-Function-Based Approach

Modulation functions have been classically applied in parameter estimation of dynamical systems to avoid the computation of derivatives of a noisy output signal (Shinbrot, 1957; Pearson, 1992; Preisig and Rippin, 1993; Unbehauen and Rao, 1998).

Definition 2. *A function $\varphi : [0, T] \mapsto \mathbb{R}$ is called a modulation function of order k if it is sufficiently smooth and if, for some fixed T, one has*

$$\varphi^{(i)}(0) = \varphi^{(i)}(T) = 0 \quad (4)$$

for all $i \in \{0, 1, \dots, k-1\}$.

Multiplication of an unknown derivative signal $y^{(i)}$ of arbitrary order i of the base signal y with such a modulation function gives by integration by parts in combination with the boundary conditions (4)

[1] Y is a vector consisting of the outputs y and their derivatives up to a certain order s. The same applies to U and F.

$$\int_0^T \varphi(\tau)y^{(i)}(\tau)\mathrm{d}\tau = \int_0^T (-1)^i \varphi^{(i)}(\tau)y(\tau)\mathrm{d}\tau \tag{5}$$

This fundamental result of modulation functions allows us to avoid the need to compute derivatives of the measured base signal and to eliminate unknown initial and final conditions of the integration which otherwise have to be considered. It has to be noted that this cannot be generalized to arbitrary functions of the derivative signal, *e.g.* $(\dot{y})^2$. However in special cases, it is possible to convert such expressions into the derivative of a function of the base signal, *e.g.* $^{\mathrm{d}}/_{\mathrm{d}t}(y^2)$, whose computation can be avoided by the considered approach based on the measured base signal only.

Over the last decades, various modulation functions have been proposed and used such as trigonometric functions $\varphi_l(t) = \sin(^{l\pi t}/_{T})^l$ as in Shinbrot (1957) and polynomial functions $\varphi_l(t) = (T-t)^l t^l$ as in Loeb and Cahen (1965), where for both cases l is of arbitrary order.

For discrete implementation with sample time T_s of such a finite-horizon integral, consider the simplest approximation of the integral (5) by the endpoint rule

$$\int_0^T (-1)^i \varphi^{(i)}(\tau)y(\tau)\mathrm{d}\tau = \sum_{k=1}^{T/T_s} (-1)^i \varphi^{(i)}(kt_k)y(kt_k)T_s \tag{6}$$

where T is a multiple of T_s and $^T/_{T_s}$ is the order of approximation. It can be easily shown, that the following linear discrete system $(A_k, b_k, c_k^\top)$ with input y realizes such an approximation of the finite-horizon integral

$$A_k = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ \vdots & & & \ddots & 1 \\ 0 & \cdots & \cdots & \cdots & 0 \end{bmatrix}, \; b_k = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix},$$

$$c_k^\top = (-1)^{(i)} \begin{bmatrix} \varphi^{(i)}(t_k) \\ \vdots \\ \varphi^{(i)}(T-t_k) \\ \varphi^{(i)}(T) \end{bmatrix} \tag{7}$$

3. PROPOSED RESIDUAL GENERATION

Instead of using the modulation function approach to avoid computation of derivatives for parameter estimation, it can also be used for residual evaluation assuming correct parameters. Without loss of generality, let us consider a single residual signal, *i.e.* P_r is scalar. Instead of the evaluation of the original residual (3), the following will be used as the residual signal

$$\bar{r}(t) = \int_{t-T}^{t} \varphi(\tau)r(\tau)\mathrm{d}\tau = \int_{t-T}^{t} \varphi(\tau)P_r(Y(\tau), U(\tau))\mathrm{d}\tau \tag{8}$$

However, avoiding the computation of derivatives of y and/or u using integration by parts is only possible if the polynomials P_r are of (or can be converted into) the following form (Pearson, 1992)

$$P_r(Y(t), U(t)) = \sum_{i=0}^{s} \frac{\mathrm{d}^i}{\mathrm{d}t^i} E_i(u(t), y(t)) \tag{9}$$

where $\frac{\mathrm{d}^i}{\mathrm{d}t^i}$ is the differential operator of order i and $E_i(u, y)$ are functions of the known input u and the measured output y. If such a form is present, then (8) can be simplified to the following expression for the adapted residual signal

$$\bar{r}(t) = \int_{t-T}^{t} \sum_{i=0}^{s} (-1)^i \varphi^i E_i(u, y)\mathrm{d}\tau \tag{10}$$

which can be evaluated without computing derivatives of the input or output signal.

The finite-horizon integral (10) can also be split into its sum of integrals (changing the order of summation and integration) which leads to the proposed residual generation as shown in Figure 2. As can be seen from Figure 2, for each derivative a linear discrete system/filter (7) with specific output vector $c_k^\top$ is needed. Design parameters of this approach are the finite horizon T over which the modulation function acts as a smoothing operator on the original residual and the order of approximation affecting the computational load.

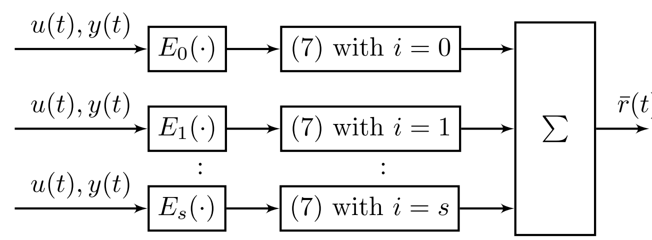

Fig. 2. Proposed residual generator using modulation functions for ARR evaluation

4. FINITE-HORIZON SENSOR FAULT DETECTION FOR PMSM

Since PMSM are very important in industry, this section will provide some background information about them. Then, the proposed residuals for sensor fault detection of PMSM will be presented.

4.1 Permanent Magnet Synchronous Motors (PMSM)

For alternating current (AC) phase systems, the currents and voltages of three-phase synchronous motors are usually expressed in a rotor-fixed (rotating) coordinate system (the d/q-frame) using the Clarke and Park Transformation. Figure 3 shows a rotating motor with angular position φ and the resulting projection of a sample stator current vector i_s onto the axes of the rotor-fixed d/q-frame.

Using these transformations, the electrical dynamics of the PMSM are commonly described as (Schröder, 1995)

$$L_d \frac{\mathrm{d}}{\mathrm{d}t} i_d = -Ri_d + p\omega L_q i_q + u_d \tag{11a}$$

$$L_q \frac{\mathrm{d}}{\mathrm{d}t} i_q = -Ri_q - p\omega L_d i_d - p\omega \Psi + u_q \tag{11b}$$

$$J\dot{\omega} = -d\omega + \frac{3p}{2}(\Psi + (L_d - L_q)i_d)i_q + \tau_d \tag{11c}$$

where i_d, i_q and u_d, u_q are the direct (in-phase) and quadrature components of the motor currents and voltages expressed in the rotor-fixed coordinates and ω is the angular velocity of the rotor. The strictly positive parameters L_d, L_q, R, Ψ, p, J and d are respectively the direct/quadrature inductance, phase resistance, flux linkage of the permanent magnet, the number of pole pairs, the rotor's moment of inertia, and the viscous friction/damping coefficient. The term τ_d represents any additional torque applied to the rotor shaft, *e.g.* the load torque, and is considered to be an unmeasured input. The state vector consists of the motor's d/q-currents and the angular speed $x = [i_d, i_q, \omega]^\top$. The output equations are $y_d = i_d + f_d$, $y_q = i_q + f_q$, and $y_\omega = \omega + f_\omega$ where each output is affected by additive sensor faults f_d, f_q, f_ω.

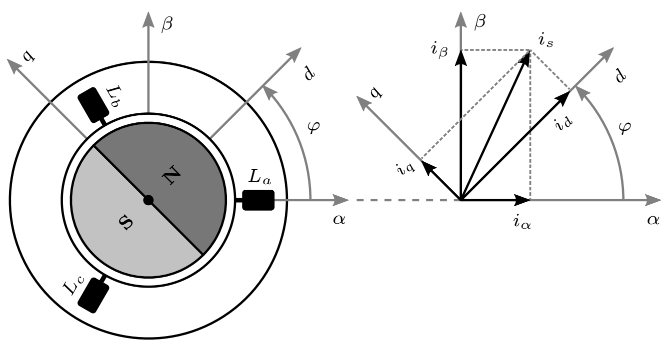

Fig. 3. Stator current expressed in rotor-fixed (rotating) d/q-frame using the Clarke and Park Transformation

4.2 Residual Generation

In order to derive the residual signals for sensor fault detection of PMSM, the steps given by Kinnaert (2003) for polynomial systems have been applied to the model of PMSM in Jahn et al. (2020). The first step is to take the first derivatives of each output. The resulting unknown quantities such as the states i_d, i_q, ω as well as the unmeasured input τ_d need to be eliminated. In Jahn et al. (2020), this has been done using Buchberger's algorithm, however other methods might be considered. After decomposition of the resulting ARR, the following residual signals $P_r(y_d, \dot{y}_d, y_q, \dot{y}_q, y_\omega, u_d, u_q) = [r_1, r_2, r_3]^\top$ have been derived

$$\begin{aligned} r_1 = &+ L_d^2 \dot{y}_d y_d + L_d \Psi \dot{y}_d + L_d R y_d^2 - L_d u_d y_d \\ &+ L_q^2 \dot{y}_q y_q + L_q R y_q^2 - L_q u_q y_q + \Psi R y_d - \Psi u_d \end{aligned} \quad (12a)$$

$$\begin{aligned} r_2 = &- p L_q^2 \dot{y}_q y_\omega - L_d L_q p^2 y_d y_\omega^2 + L_q p u_q y_\omega \\ &- L_d R \dot{y}_d - L_q \Psi p^2 y_\omega^2 - R^2 y_d + R u_d \end{aligned} \quad (12b)$$

$$\begin{aligned} r_3 = &+ p L_d^2 \dot{y}_d y_\omega - L_d L_q p^2 y_q y_\omega^2 - L_d p u_d y_\omega \\ &- L_q R \dot{y}_q - \Psi R p y_\omega - R^2 y_q + R u_q \end{aligned} \quad (12c)$$

As explained in Section 3, the modulation function approach can be used to avoid the computation of the derivatives of the system's outputs y_d and y_q needed for the residuals in Equation (12). However, none of the original residuals as given by (12) are in the required form of (9). If possible, they need to be converted before further use.

In case of the first residual r_1, the terms $\dot{y}_d y_d$ and $\dot{y}_q y_q$ do not satisfy the requirements. However, using the following equality

$$\dot{y}_{d,q} y_{d,q} = \frac{1}{2} \frac{\mathrm{d}}{\mathrm{d}t} (y_{d,q}^2) \quad (13)$$

these terms can easily be converted. In case of the second residual r_2, the first term does not fit the required form (9). However, the product rule of derivation gives

$$\dot{y}_q y_\omega = \frac{\mathrm{d}}{\mathrm{d}t} (y_q y_\omega) - y_q \dot{y}_\omega \quad (14)$$

Therefore, if we assume stationary operation of the PMSM, *i.e.* $\dot{\omega} = 0$, and thus in the fault free case $\dot{y}_\omega = 0$, this allows the second residual to be used in the modulation function-based-approach. In case of the third residual, the same argument applies.

In order to complete the residual generator design, the final expressions which need to be evaluated during run time for the sensor fault detection are given by

$$\begin{aligned} \bar{r}_1 = \int_{t-T}^{t} &- \dot{\varphi}(L_d^2 y_d^2 + L_q^2 y_q^2 + L_d \Psi y_d) \\ &+ \varphi(L_d R y_d^2 - L_d u_d y_d + L_q R y_q^2 \\ &- L_q u_q y_q + \Psi R y_d - \Psi u_d) \, \mathrm{d}\tau \end{aligned} \quad (15a)$$

$$\begin{aligned} \bar{r}_2 = \int_{t-T}^{t} &- \dot{\varphi}(-p L_q^2 y_q y_\omega - L_d R y_d) \\ &+ \varphi(-L_d L_q p^2 y_d y_\omega^2 + L_q p u_q y_\omega \\ &- L_q \Psi p^2 y_\omega^2 - R^2 y_d + R u_d) \, \mathrm{d}\tau \end{aligned} \quad (15b)$$

$$\begin{aligned} \bar{r}_3 = \int_{t-T}^{t} &- \dot{\varphi}(+p L_d^2 y_d y_\omega - L_q R y_q) \\ &+ \varphi(-L_d L_q p^2 y_q y_\omega^2 - L_d p u_d y_\omega \\ &- \Psi R p y_\omega - R^2 y_q + R u_q) \, \mathrm{d}\tau \end{aligned} \quad (15c)$$

where none of the derivatives of the outputs y_d or y_q are needed anymore.

4.3 Residual Evaluation and Decision Making

In practical situations, the residual signals will deviate from zero due to measurement noise and modeling errors. Therefore, when performing residual evaluation, it is necessary to introduce a threshold below which the residual is considered to be inactive. Such a threshold can be determined using simulations with noisy measurements and/or actual plant measurements.

Table 1. Effect of faults on each individual residual signal (Jahn et al., 2020)

	f_d	f_q	f_ω
r_1	x	x	
r_2	x		x
r_3		x	x

Once specific residuals are assessed as being active, Table 1 decodes the combination of residuals to the corresponding fault action. Each column specifies which residuals correspond to which individual fault. For example, assume that residuals r_2 and r_3 are active (*i.e.* above the relevant threshold) while r_1 is inactive. The second column states that fault f_ω must have occurred. For a more detailed discussion on fault isolation and multiple occurring faults refer to Jahn et al. (2020).

5. SIMULATION STUDIES

The proposed FDI method is simulated for a speed-controlled salient-pole PMSM with parameters given in Table 2. The control strategy follows a classical field-orientated vector control law with current set points chosen according to the motor's maximum-torque-per-current (MTPC) curve.

Table 2. Parameters of PMSM

parameter	value
phase resistance - R	$9.25\,\mathrm{m\Omega}$
d-axis inductance - L_d	$0.895\,\mu\mathrm{H}$
q-axis inductance - L_q	$1.044\,\mu\mathrm{H}$
flux linkage - Ψ	$4.8751\,\mathrm{mWb}$
pole pairs - p	5
rotor inertia - J	$0.0113\,\mathrm{N\,m\,s^2}$
friction coefficient - d	$0.002\,\mathrm{N\,m\,s\,rad^{-1}}$

The control and FDI algorithms are simulated to run at a fixed sampling rate of $T_s = 0.1\,\mathrm{ms}$ while the plant is modeled continuously and numerically solved using the Dormand-Prince method (ode45) with variable step size. A polynomial modulation function is chosen $\varphi(t) = (T - t)^2 t^2$. The finite horizon integration is implemented using a discrete linear system approximation as explained in Subsection 2.2 running at $5\,T_s = 0.5\,\mathrm{ms}$. The finite horizon is designed to be $T = 50\,\mathrm{ms}$, resulting in an approximation order of 100 for the chosen sample time.

In this simulation, it is assumed that the speed can be measured and does not need to be estimated based on position measurements. Gaussian white noise by means of a random number generator with a normal distribution $\mathcal{N}(0, \sigma^2)$ at a sampling rate of $0.1\,\mathrm{ms}$ has been added as sensor noise. The selected variances are $\sigma_i^2 = 0.5\,\mathrm{A}^2$ and $\sigma_\omega^2 = 1.5\,\mathrm{rpm}^2\,(\mathrm{min}^{-2})$ for the d/q-currents and speed sensor, respectively. Initially, the motor is accelerated to a target speed of $1800\,\mathrm{rpm}\,(\mathrm{min}^{-1})$. At $t = 2\,\mathrm{s}$, an external load torque of $1.2\,\mathrm{N\,m}$ is applied to the motor such that a $45\,\mathrm{A}$ phase current is present at steady state. In the interval $t = [4, 5)\,\mathrm{s}$, sensor fault $f_d = 4\,\mathrm{A}$ is active. In the following time interval $t = [5, 6)\,\mathrm{s}$, sensor fault $f_q = 30\,\mathrm{A}$ becomes active, while in the final time interval $t = [6, 7)\,\mathrm{s}$, sensor fault $f_\omega = 250\,\mathrm{rpm}\,(\mathrm{min}^{-1})$ is active.

Figure 4 shows the simulation results in combination with the results of residual generation based on robust exact differentiation (Jahn et al., 2020). As can be clearly seen, the influence of the measurement noise on the residuals is much lower in case of a modulation-function-based approach compared to the residuals based on robust exact differentiation. Since the width of the noise band has been significantly reduced, the introduction of a suitable threshold for each residual (above the noise band and below the active fault level) is less challenging, which makes the decision making process easier. On the other hand, the modulation-function-based residuals can handle more measurement noise before a threshold-based decision making becomes unfeasible due to the noise band overlap. However, this comes at the main drawback of having delayed residual reaction to fault actions. To emphasize this, Figure 5 shows a close-up of the residual signals over the time period when the first fault is introduced.

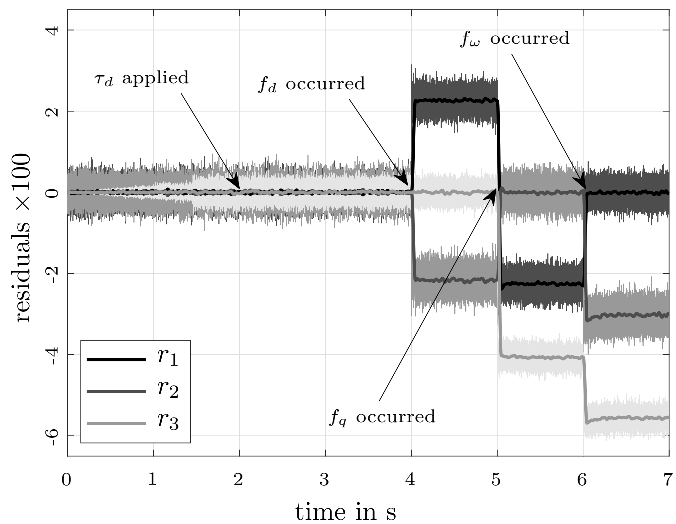

Fig. 4. Residual signals during motor run and sensor faults

As can be seen the residuals need $T = 50\,\mathrm{ms}$ to reach the active fault level. Therefore, the finite horizon time T needs to be chosen according to how fast relevant faults can appear/disappear in order to be able to detect them.

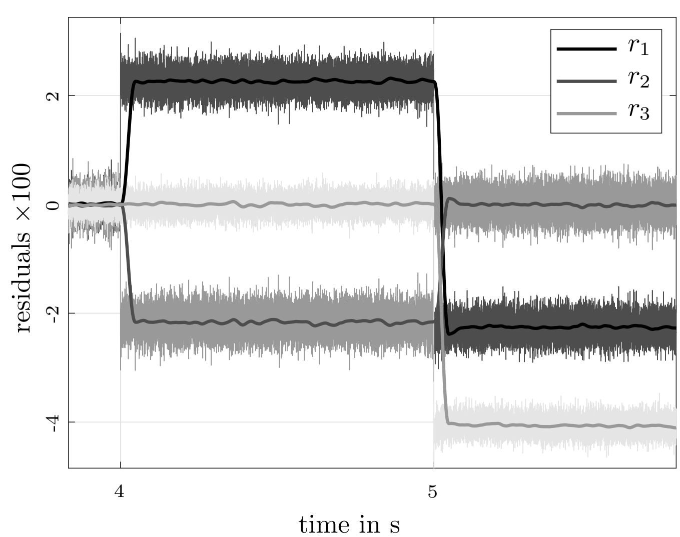

Fig. 5. Close-up of the residual signals after the first fault was introduced

6. CONCLUSION AND FUTURE WORK

This paper has presented the design of a residual generator for sensor fault detection of PMSM. The main contribution is to combine residual generation based on the parity-space-based approach with a modulation-function-based approach in order to derive a residual signal filtered over a finite horizon. This property helps to reduce the influence of noise on the residuals facilitating the decision making while preserving the benefit of finite response time as for the approach based on robust exact differentiation. The result has been applied to a model of a PMSM. Simulation results show that speed and current sensor faults can be detected and that the influence of noise on the residuals has been reduced.

In order to evaluate the performance of a PMSM under real conditions, the next step is to apply the proposed method to a real PMSM. Furthermore, the impact of using phase current sensors and position sensors, which are commonly used in industrial applications of PMSM, on the proposed FDI needs to be further investigated.

REFERENCES

E. A. Arnold. Modular algorithms for computing Gröbner bases. *Journal of Symbolic Computation*, 35(4):403 – 419, 2003. ISSN 0747-7171. doi: 10.1016/S0747-7171(02)00140-2.

M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, Heidelberg, 3rd edition, 2015. ISBN 978-3-662-47942-1.

B. Buchberger. Gröbner bases: An algorithmic method in polynomial ideal theory. In N. K. Bose, editor, *Multidimensional Systems Theory and Applications*, pages 89–127. Springer Netherlands, Dordrecht, 1985. ISBN 978-94-017-0275-1. doi: 10.1007/978-94-017-0275-1_4.

J. Chen, P. M. Frank, M. Kinnaert, J. Lunze, and R. J. Patton. Fault detection and isolation. In Karl Åström, Pedro Albertos, Mogens Blanke, Alberto Isidori, Walter Schaufelberger, and Ricardo Sanz, editors, *Control of Complex Systems*, pages 191–207. Springer London, London, 2001. ISBN 978-1-4471-0349-3. doi: 10.1007/978-1-4471-0349-3_9.

Zhiwen Chen, Steven X. Ding, Kai Zhang, Zhebin Li, and Zhikun Hu. Canonical correlation analysis-based fault detection methods with application to alumina evaporation process. *Control Engineering Practice*, 46:51 – 58, 2016. ISSN 0967-0661. doi: 10.1016/j.conengprac.2015.10.006.

Zhiwen Chen, Kai Zhang, Yuri A.W. Shardt, Steven X. Ding, Xu Yang, Chunhua Yang, and Tao Peng. Comparison of two basic statistics for fault detection and process monitoring. *IFAC-PapersOnLine*, 50(1):14776 – 14781, 2017. ISSN 2405-8963. doi: 10.1016/j.ifacol.2017.08.2586. 20th IFAC World Congress.

E. Chow and A. Willsky. Analytical redundancy and the design of robust failure detection systems. *IEEE Transactions on Automatic Control*, 29(7):603–614, July 1984. ISSN 0018-9286. doi: 10.1109/TAC.1984.1103593.

S. X. Ding. *Model-based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools*. Springer Publishing Company, Incorporated, 1st edition, 2008. ISBN 9783540763031.

S. X. Ding. Data-driven design of monitoring and diagnosis systems for dynamic processes: A review of subspace technique based schemes and some recent results. *Journal of Process Control*, 24(2):431–449, 2014. ISSN 0959-1524. doi: 10.1016/j.jprocont.2013.08.011. ADCHEM 2012 Special Issue.

Paul M. Frank. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. *Automatica*, 26(3):459 – 474, 1990. ISSN 0005-1098. doi: 10.1016/0005-1098(90)90018-D.

Changsheng Hua, Steven X. Ding, and Yuri A.W. Shardt. A new method for fault tolerant control through Q-learning. *IFAC-PapersOnLine*, 51(24):38 – 45, 2018. ISSN 2405-8963. doi: 10.1016/j.ifacol.2018.09.526. 10th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS 2018.

A. Isidori, M. Kinnaert, V. Cocquempot, C. De Persis, P. M. Frank, and D. N. Shields. Residual generation for FDI in non-linear systems. In Karl Åström, Pedro Albertos, Mogens Blanke, Alberto Isidori, Walter Schaufelberger, and Ricardo Sanz, editors, *Control of Complex Systems*, pages 209–227. Springer London, London, 2001. ISBN 978-1-4471-0349-3. doi: 10.1007/978-1-4471-0349-3_10.

B. Jahn, M. Brückner, S. Gerber, and Y. A.W. Shardt. Sensor fault detection for salient pmsm based on parity-space residual generation and robust exact differentiation. *IFAC-PapersOnLine*, 53(2):86–91, 2020. ISSN 2405-8963. doi: 10.1016/j.ifacol.2020.12.099. 21th IFAC World Congress.

Yuchen Jiang, Shen Yin, and Okyay Kaynak. Optimized design of parity relation-based residual generator for fault detection: Data-driven approaches. *IEEE Transactions on Industrial Informatics*, 17(2):1449–1458, 2021. doi: 10.1109/TII.2020.2987840.

M. Kinnaert. Fault diagnosis based on analytical models for linear and nonlinear systems - a tutorial. *IFAC Proceedings Volumes*, 36(5):37 – 50, 2003. ISSN 1474-6670. doi: 10.1016/S1474-6670(17)36468-6. 5th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes 2003, Washington DC, 9-11 June 1997.

A. Levant. Higher-order sliding modes, differentiation and output-feedback control. *International Journal of Control*, 76(9-10):924–941, 2003. doi: 10.1080/0020717031000099029.

J. Loeb and G. Cahen. More about process identification. *IEEE Transactions on Automatic Control*, 10(3):359–361, 1965.

A. E. Pearson. Explicit parameter identification for a class of nonlinear input/output differential operator models. In *[1992] Proceedings of the 31st IEEE Conference on Decision and Control*, pages 3656–3660 vol.4, Dec 1992. doi: 10.1109/CDC.1992.370969.

H.A. Preisig and D.W.T. Rippin. Theory and application of the modulating function method—i. review and theory of the method and theory of the spline-type modulating functions. *Computers & Chemical Engineering*, 17(1):1 – 16, 1993. ISSN 0098-1354. doi: 10.1016/0098-1354(93)80001-4. An international journal of computer applications in chemical engineering.

S. Joe Qin. Survey on data-driven industrial process monitoring and diagnosis. *Annual Reviews in Control*, 36(2):220 – 234, 2012. ISSN 1367-5788. doi: 10.1016/j.arcontrol.2012.09.004.

J. F. Ritt. *Differential Algebra*. Colloquium publications. American Mathematical Society, 1950. ISBN 9780821846384.

D. Schröder. *Elektrische Antriebe - Regelung von Antriebssystemen [Electrical drives - control of drive systems]*. Springer Berlin Heidelberg, 1995. ISBN 9783642300950.

M. Shinbrot. On the analysis of linear and nonlinear dynamical systems from transient-response data. *Transactions ASME*, 79(3):547 – 552, 1957.

H. Unbehauen and G.P. Rao. A review of identification in continuous-time systems. *Annual Reviews in Control*, 22:145 – 171, 1998. ISSN 1367-5788. doi: 10.1016/S1367-5788(98)00015-7.