Current Sensor Fault Detection and Isolation in Doubly Fed Induction Generator

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Abstract. Fault Detection and Isolation (FDI) is gaining interest as a means to increase the reliability and availability of efficient systems. Measuring sensors used for data acquisition are more prone to failures. The main objective of this paper is to provide model based FDI for current sensor fault closed-loop controlled Doubly Fed Induction Generator (DFIG) model connected to power grid. The sensor fault was detected and isolated by two methods including Unknown Input Observer (UIO) on reduced order DFIG model and fuzzy logic. The results show improvement in computational speed during online monitoring when the fault isolation is performed on reduced order models.

Keywords: Model reduction, doubly fed induction machine, Unknown input observers, sensor fault, fuzzy logic.

1. Introduction
The information related to electrical signals (current, voltage) and position are received from appropriate sensors for control of electric drives. Sensor abnormalities highly influence the reliability of the controlled system [1]-[2]. The Fault Detection and Isolation (FDI) system identify fault in the monitored system and generates alarm. It also identifies the fault location. Detection of fault at an early stage is critical inorder to avoid damage to the machine. The accurate and fast fault diagnosis helps to make decisions on corrective actions and repairs. This can minimize downtime, increase the safety of plant operations and reduce manufacturing costs.

An automatic control system that handles fault occurring in the system is composed of many components including sensors, actuators and the process itself. Each component is subjected to unknown inputs that are alleged as measurement noise and process noise. Also, external disturbances act on the system. In model-based fault diagnosis the mismatch between the plant and the developed mathematical model are also considered as unknown input. The faults influencing the system are actuator faults, component (or process) faults, and sensor faults. Sensor faults are the discrepancies between measured and actual plant variable. It do not directly affect the process but seems to influence only if the sensor measurements aids to generate the acting signal by the controller. These faults
may occur due to over usage without proper recalibration, wear and tear or total failure. These faults are additive type (independent of the measured magnitude). Certain faults such as total sensor failure or sticking are multiplicative faults.

In general, the main intention in any FDI scheme is to neglect the transient response in any system behavior and consider only the steady state response. This insists the need in separating the steady state dynamics. A mathematical model with fewer number of state variables are developed to capture the steady state dynamics of the system. Hence model order reduction is considered as the initial step in model based FDI procedures. Friedrich W.Fuchs et al [7] has discussed model based sensor fault detection and isolation in Doubly Fed Induction Generator (DFIG). Fikret Caliskan [8] has performed FDI using Unknown Input Observers (UIO). Li et.al [3] have given a review on the recent advancements in sensor fault diagnosis, in which it has been summarized that one of the most promising method out of the different advanced technologies that are developed to reduce computation complexity in fault diagnosis is rule based or fuzzy inference based intelligent systems. This method excels if the fuzzy knowledge base is complete. Heydarzadeh et al. [4] has suggested that the residual evaluation based on fuzzy-logic prevents false alarms in fault diagnosis.

In view of above, this work presents two different approaches in current sensor fault diagnosis in DFIG. In the first approach, UIO has been designed based on reduced model order of DFIG to identify the faulty sensor. In the second approach fuzzy logic based FDI is implemented for detecting and isolating sensor fault in DFIG.

2. Doubly fed induction generator

The control structure of DFIG includes stator coil which is connected to the grid directly and the rotor coil is supplied with varying DC voltage and frequency. The rotor current is field controlled. Stator active power and reactive power is controlled independently. The speed of AC machine controlled for laboratory tests.

The electrical model of the DFIG system [7] is described in state space as shown in Eq. (1). In general induction machines are considered to be non-linear as the back electromotive force relies on the angular speed of rotor $\omega_m$. However, $\omega_m$ is a variable and hence the non-linear system matrix is split into two parts Ao, which constitutes the linear parameters in relation to states and A1 constitutes parameters that are linear with $\omega_m$. The frequency of rotation with respect to the reference frame is denoted as $\omega_A$ and the pole pairs as p. The resistances and inductances of the stator and rotor are represented as RS, RR, LS, LR respectively. M refers to the mutual inductance. The states of the model are the stator current and rotor current. The stator voltage and rotor voltage are inputs to the model. The stator quantity of direct axes is denoted by subscript Sd and the corresponding quadrature axes is denoted by subscript Sq. Similarly the rotor quantity of direct axes is denoted by subscript Rd and the and the corresponding quadrature axes is denoted by subscript Rq.
3. Sensor Fault Detection And Isolation

The stator and rotor currents of DFIG are measured by appropriate current sensors. These sensors are subjected to faults such as bias, drift, precision degradation etc. Hence detecting fault in sensors becomes essential especially for electric drives operating at variable speed.

Inspite of the various methodologies that are adopted for sensor fault detection and isolation, a common way adopted for industrial applications are hardware redundancy. It compares the individual hardware outputs are compared its consistency is cross checked. However, this method is quite infeasible as the cost of implementation would be high. Another approach referred as analytic redundancy apply both functional and analytic details regarding the system using a mathematical model which is termed as model-based FDI.

In model-based FDI, the outputs of the system are estimated which also should satisfy robustness and sensitivity. In recent years, different approaches have been developed to address the robustness of fault detection estimators. This includes Unknown Input Observers (UIO), Kalman filters, $H_2/H_\infty$ filters. Fault detection has two modules i) residual generation and ii) decision making. Residuals give the discrepancies between true values of system variables and the defined mathematical model in faulty conditions. However, residuals are influenced by errors in modeling, disturbance and noise. A large variety of statistical analysis may be applied on residuals [14]. False alarms in fault detection is usually avoided by fixing very high threshold levels. The uncertainties in system modeling may lead to either high or low threshold levels and hence adaptive thresholds are devised [15]. A satisfactory design of the residual generator permits fault isolation and hence fault classification by projecting the residual vector to specific fault case. The different ways in residual generation are parity equations [12], observers [9][10][11] and parameter estimation [13]. The decision module evaluates the reliability of each residual, as well as the decision risk. This implies conservative criteria, and hence the computational time in fault diagnosis is increased.

In the context of model-based fault detection, the design of the residual generators is based on reduced-order models so as to make it suitable for practical implementation. Inspite of the errors due to model approximation that are intrinsic in the reduced-order models, it is important that designed estimator discriminate between approximation errors and faults.
A. Unknown Input Observer

The fault and the disturbance signals acting on a system are generally unknown and hence UIO is considered as a useful method [20]. In design of UIO, the uncertainties of the system dynamics are introduced as an additive term as given in Eq. (2)

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\
y(t) &= Cx(t)
\end{align*}
\]  

Eq. (2)

\(x(t) \in \mathbb{R}^n\) and \(y(t) \in \mathbb{R}^m\) refers to state vector and output vector respectively. \(u(t) \in \mathbb{R}^r\) and \(d(t) \in \mathbb{R}^q\) refers to the known input vector and unknown input vector respectively. The observer defined by Eq. (2) is recognized as UIO if the estimation error i.e. \(e(t) = y(t) - \hat{y}(t)\) asymptotically tends to zero, ignoring the disturbances or unknown inputs of the system. Fig. 1 shows the structure of a full order unknown input observer.

![Block diagram of full order UIO](image)

\textbf{Fig 1.} Block diagram of full order UIO

The equations governing the observer as obtained from the block diagram is in (3)

\[
\begin{align*}
\dot{z} &= Fz + TBu + Ky \\
\hat{x} &= z + Hy
\end{align*}
\]  

Eq. (3)

Where \(z \in \mathbb{R}^n\) refers to the estimated states and \(z \in \mathbb{R}^n\) refers to the states of UIO and the matrices \(K, T, H, \) and \(F\) are required to design the observer for decoupling unknown input as in (4).

\[
\begin{align*}
K &= k_1 + k_2 \\
HC - DE &= 0 \\
T &= I - HC \\
F &= A - HCA - CK_2 \\
k_3 &= FH
\end{align*}
\]  

Eq. (4)

The rotor and stator current sensor fault detection and isolation scheme adopted is shown in Fig. 2. General Unknown Input Observer (GUIO) is used to generate fault residual which is an indicator of sensor faults.

![Fault detection and isolation scheme](image)

\textbf{Fig 2.} Fault detection and isolation scheme
B. Fuzzy logic
Fault isolation was also performed by using fuzzy logic. The necessary steps in fault isolation [19] are as given:

1) The state space representation of the system is developed from the differential equations governing the system.

2) The response of the model in frequency domain is obtained for no fault case and different fault cases. The corresponding Markov parameters are determined and accumulated in fault dictionary.

3) The extracted features in the fault dictionary act as input to a Fuzzy Inference System (FIS) based on Mamdani rules for isolation of fault.

The basic structure of fuzzy system is shown in Fig. 3 [20]. The Markov parameters that were determined for fault free condition and faulty cases are given as crisp inputs to the fuzzifier. The membership functions quantifies the linguistic terms. The IF-Then rules by the experts are accumulated in knowledge base. The inference engine generates fuzzy output using the rules stored in knowledge base.

The output from the fuzzy inference engine is again converted to crisp values in a defuzzifier. It uses the membership functions corresponding to the functions used in the fuzzifier. The most commonly used defuzzifying techniques are centroid method, center of sums and mean of maximum. Mamdani rule base is commonly used for incarcerating expert knowledge and also it permits us to explain the knowledge in more instinctive and humanlike manner. Mamdani style fuzzy models are exemplified with antecedents and consequences as combined propositions which incorporate logical connectives AND and OR. The rule $i^{th}$ of a rule base in Mamdani systems is

$$\text{IF } x_1 \text{ is } A_{11} \text{ AND } \ldots \text{AND } x_p \text{ is } A_{1p} \text{ THEN } y = y_i$$

The inference for each rule is calculated as

$$\mu_i(x_1) = \min\left[\mu_{11}(x_1), \mu_{12}(x_1), \ldots, \mu_{1p}(x_1)\right]$$

In this paper max-min composition and defuzzification using centroid method is used.

4. Results And Discussion
The steady state value of DFIG power is 22 kW and stator coil is fed by 400 V. The machine parameters are shown in Table 1.

| S.No. | Parameters | Values   |
|-------|------------|----------|
| 1     | $R_S$      | 113m$\Omega$ |
| 2     | $R_R$      | 110m$\Omega$ |
| 3     | $L_S$      | 46.8mH    |
| 4     | $L_R$      | 46.8mH    |
| 5     | $M$        | 45.8mH    |

In the state space representation of the model equation given in Eq. (1) the system matrix, input and output matrix is numerically given as
As an initial step of fault detection residuals are generated based on reduced order models. Model reduction was originally proposed by Davison et.al [17]. The eigen values of the state space model of full order can be ignored if they are far away from the origin and those eigen values that are close to the origin alone can be retained. Hence the reduced order model has only dominant time constants. By inspection of the eigen values and the eigen vectors associated, the dominates states are $I_{\text{sd}}$ and $I_{\text{rq}}$.

A model order reduction is performed using Selective Modal Analysis (SMA) [5][6][16]. The reduced system has eigen values close to the eigen values of the full order model. The Bode magnitude plot of the reduced order and full order DFIG models are found to be similar as shown in Fig. 4.

![Bode Diagram](image)

**Fig 4:** Bode plot comparison of actual system with reduced order system using SMA

Unknown input observer is designed for reduced order DFIG using algorithm in [8] and fault in rotor current sensor is isolated. Residual is generated when no fault in either sensors which is shown in Fig 5a, it can be seen that both rotor and stator current residuals have value close to zero. It is not exactly zero due to model inaccuracies. When bias fault introduced in rotor current sensor fault the residual corresponding to it has increased to 1.1 as shown in Fig 5b. The isolated sensor fault using the isolation logic as in Fig 2 for a fixed threshold of half the peak current value is given in Fig 6 which displays logical 1 indicating fault in rotor current sensor.
The rotor and stator current sensor outputs are assumed to vary by 25% from their true value for single fault cases and Markov parameter of the state space model for no fault and single fault cases are determined from the frequency response. This information is used to develop single input single output Madmani system for fuzzy based fault isolation. Fig 7a and Fig. 7b shows the isolation of fault in no sensor fault case and fault in 3rd sensor respectively.

Fig 5. a) Residual with fault b) Residual without fault

Fig 6. Isolated fault of rotor current sensor
\[
\begin{align*}
\text{sys} &= \{'\text{dfiz}'\}, \\
\text{type} &= \{'\text{mamdani}'\}, \\
\text{andMethod} &= \{'\text{min}'\}, \\
\text{orMethod} &= \{'\text{max}'\}, \\
\text{defuzzMethod} &= \{'\text{centroid}'\}, \\
\text{inpMethod} &= \{'\text{min}'\}, \\
\text{aggMethod} &= \{'\text{max}'\}, \\
\text{input} &= [], \\
\text{output} &= [], \\
\text{rule} &= [] \end{align*}
\]

\[
\text{rulelist} = \\
\begin{array}{cccc}
1 & 1 & 1 & 1 \\
2 & 2 & 1 & 1 \\
3 & 3 & 1 & 1 \\
4 & 4 & 1 & 1 \\
5 & 5 & 1 & 1 \\
\end{array}
\]

\[
\text{out} = 1
\]

\text{NO}
\text{NO FAULT}

\[
\begin{align*}
corr = 0.179 \\
corr = 0.55
\end{align*}
\]
5. Conclusion

Current sensor fault detection and isolation based on the mathematical model of doubly fed induction generator has been designed using unknown input observer and fuzzy logic. It has been inferred that FDI scheme applied on reduced order model improve the computational speed during online monitoring. The future scope is to analyze sensor fault and other type of possible fault which uses adaptive threshold technique to take care of inaccuracy that may arise due to linearization, or model order reduction, which can be applied to detect even faults of small magnitude.

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Fig 7. FDI using fuzzy logic (a) No fault (b) Fault in sensor 3
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