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KALMAN FILTER-BASED FAULT-DIAGNOSIS SCHEME FOR DC MOTOR

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Abstract

For engineering systems in industrial applications, fault detection and diagnostics are critical. A considerable number of primary and secondary protection devices are fitted on industrial instruments. However, for the system to operate safely, it must be closely monitored. Many real-world systems are non-linear in nature, and they are influenced by stochastic noises and disturbances. As a result, failure identification of such systems is critical. In this paper, model-based state estimate methodologies are used to enable predictive maintenance and carry out fault detection for a DC motor model. Kalman Filter and Internal-model based Kalman Filter are two model-based estimate techniques examined. Various faults such as bearing fault, inertia fault, short-circuit and open-circuit faults are explored. The results demonstrate that Internal-model based Kalman performs better in fault identification for various fault conditions.

Keywords: DC motor, Kalman Filter, identification, detector, fault, internal model

1. Introduction

Modern manufacturing processes can benefit from early and precise fault identification and diagnosis, which can improve plant safety and lower costs. These types of process monitoring approaches are frequently used in real-world industrial systems. A fault is defined as a deviation from usual behavior of at least one system parameter or property. It causes the system to fail or malfunction, and it can transform a linear system into a highly nonlinear system as noises and disturbances are introduced. FDD for dynamic systems has been acknowledged as a critical component in enhancing the reliability of practical control systems. It is a method of detecting faults in physical systems while attempting to determine the cause of the faults [6-8].

FDD's basic technique consists of four critical processes: fault detection, isolation, identification, and evaluation. When a fault occurs in the system, it is separated and categorized based on the type of issue, its position, and the amount of time it takes to find it. While there are various distinct ways for detecting problems, they all fall into one of 3 classifications. There are three types of models: qualitative, process history, and quantitative. Model-based approach utilises the analytical model of the system which reflects the most profound and concise knowledge of the system. Qualitative and process history-based approaches create regression models and other pattern identification methods from vast amounts of historical data, with or without engineering knowledge [1-3].

A DC propeller was a machine that transforms electrical power into mechanical power. When a power carrying circuit is put in a magnetization, it senses a mechanical power. This is the basis behind DC motors. For systems needing a strong starting power, DC motors are perfect. They're also useful for applications including reactive braking and backing, which are common in industrial settings. Internal changes can cause a DC motor to fail during operation which can be potentially hazardous. All electric motors have a fixed life duration that is dependent on regular maintenance; otherwise, they are more likely to fail much sooner. The calculated model parameters can be used to determine the electromechanical properties of the motor. Motor faults are detected by measuring the changes in electromechanical characteristics. Various faults are investigated, including bearing faults, inertia faults, short-circuit faults, and open-circuit faults.

Engineers and scientists are increasingly interested in fault diagnosis and analysis of DC motors in digital surveillance and quality management. The numerous approaches used in fault identification, and also the types of defects treated with in the DC motor design, are shown in some of the scientific projects mentioned here. [4] developed a geometric technique for identifying and diagnosing nonlinear system defects. This paper presents a differential geometric method to the issue of linear system fault discovery and separation. The main topic of discussion in this paper is filter architecture. [9] proposed a sensor failure monitoring and diagnosis scheme for an unknown linear time-invariant neutrality delay network. The defect estimate is demonstrated to be consistently limited, as are the condition and output error terms. [11] discussed electric machines predictive maintenance and problem diagnosis. This document provides a brief overview of bearing, rotor, stator, and eccentricity-related defects and their treatment.

[13] presented a modified approach to observer-based defect identification. The fault indicator used in this study is not affected by observer benefit, which is a practical and advantageous change to a spectator fault identification method. Observer gain was used in observer-based strategies to get total quantified fault data residual. This study uses a DC motor as an instance to demonstrate the efficacy of the revised observer leftover as a failure signal. [2] described real-time fault diagnosis for a DC motor powering a mechanical actuator system. This research uses single-phase currents and algorithms to identify electrical modifications in the motor.

[16] proposed a Kalman filter and an inner model principle-based method for parametric defect identification. The author demonstrates that an IMP-KF structure can be utilised to detect parametric defects and that it is both a sufficient and necessary condition for obtaining residuals in this study. [18] explains the contrast of 4 state observer architecture options for MIMO systems. A controlled and viewable DC servo motor was employed as a MIMO prototype in this study. A full order uncertain output and input architecture is used to produce residuals which can be used to identify defects. When developing the output and input observers, the unknown consistent fluctuations of parameter were

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considered into account. A failure identification and diagnostic technique for DC motors based on models is proposed. [14] employed a Kalman filter to detect faults. In this research, incipient defect is taken into account. For fault detection, the Kalman filter algorithm has been used with residual estimates, and the shift in residues for the present signal is detected.

[5] described a state estimation study on a DC motor utilizing a Kalman filter for predictive servicing. On a DC motor, the outcomes of a failure prevention strategy using state prediction with a Kalman filter were presented. The motor's spinning velocity was constantly calculated and documented every 5 mins. The measurement values was used to execute Kalman prediction and verify that the prediction was correct. The purpose of this research is to prevent failure in the short term in order to increase dependability by using the Kalman filter to estimate state for predictive maintenance. Advocated using a Kalman filter to model the detection, confirmation, and diagnosis of incipient faults. This work presents a model-based problem diagnosis, identification, and confirmation in a DC motor. A comparison is made and the performance is tested by building a healthy and malfunctioning DC motor model. A study on defect identification, isolation, and reconfiguration methodologies was given in [15]. Several model-based methodologies for creating noise- and disturbance-resistant residuals are discussed in this paper [12].

In this paper, Kalman Filter (KF) which is a model-based estimation approach is used. The Kalman filter is a state space model-based optimal estimator or optimal recursive data processing algorithm. The Kalman filter aids in estimating system state behaviour in the past, present, and future. The Kalman Filter is a more advanced smoothing method that adapts to changes in various parameters in real time. A variant of Kalman filter is built using internal-model approach which establishes the necessary and sufficient condition for the tracking the output of a dynamic system. Both the algorithms are applied to DC motor model under various fault conditions and the residuals are generated. Based on the residuals, fault detection and identification is carried out.

2. DC Motor modelling

2.1 Mathematical modelling

The stator and armature are the 2 major components of a DC motor. The armature represents the revolving component, whereas the stator represents the fixed component. The DC supply is linked to the armature coil. Commutators and brushes make up the armature coil. Brushes transport electricity from the rotating component of the motor to the static external load via the commutator, which converts AC to DC. The goal of creating a statistical equation is to establish a link between the applied voltage and the motor velocity. The electrical and mechanical characteristics of a DC motor can be used to generate two balance equations. Finally, the two balancing equations are used to create a state space model. The specifications of a 12V DC motor are used to build the DC motor modelling.

The voltage source Va is illustrated across the coil of the armature in the analogous electrical system of a DC motor depicted in (**Figure.1 Circuit Diagram of DC motor**). An inductance L a, in parallel with a resistance R a, in series with an electric potential that opposes the voltage supply, can be used to represent the electrical equal of the armature coil. The induced voltage was produced by the spinning of the electrical coil through the permanent magnets' fixed flux lines. The back emf is a term used to describe the voltage.

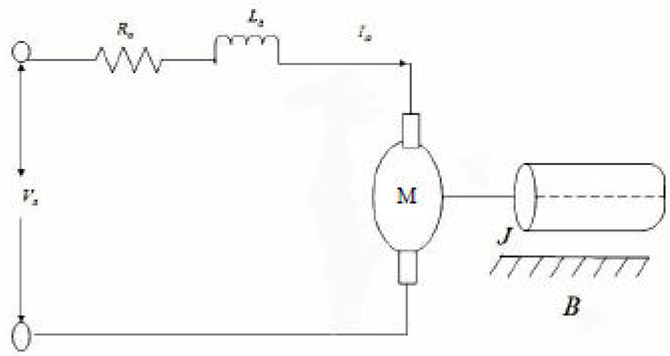

Figure.1 Circuit Diagram of DC motor

Using Kirchoff's law, voltage is given by

$$V_a - V_{Ra} - V_{La} - V_c = 0 \tag{1}$$

The armature voltage is V a, the voltage drop across the inductor and resistor is V Ra and V La, and the back emf is V c.

The back emf can be expressed as follows:

$$V_c = K_v \, \omega_a \tag{2}$$

Where K v represents the velocity characteristic or back emf constant, which is controlled by the flow velocity of the constant magnets, the armature's iron core reluctance, and the no. of turns in the winding. The armature's rotating velocity is _a. As a result, eqn.(1) becomes, with current i a.

$$V_a - i_a R_a - L_a \frac{di_a}{dt} - K_v \, \omega_a = 0 \tag{3}$$

To achieve energy balance in the system, the sum of the motor's torques should equal zero. Electromagnetic torque 〖T〗 e, torque owing to motor rotational speed T ω1 , torque due to rotor speed T_ω, and torque due to mechanical load T L are the torques involved.

$$T_e - T_{\omega 1} - T_\omega - T_L = 0 \tag{4}$$

Eqn. (4), can be written as

$$K_t i_a - J\frac{d\omega_a}{dt} - B\omega_a - T_L = 0 \tag{5}$$

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Where K t represents the torque constant, J represents the rotor's inertia and the equivalent mechanical load, and B represents the damping factor or friction coefficient.
From eqns. (3) and (5), the mathematical formulation for the DC motor model may be rearranged as,

$$\frac{di_a}{dt} = \frac{V_a}{L_a} - \frac{R_a}{L_a} i_a - \frac{K_v}{L_a} \omega_a \tag{6}$$

$$\frac{d\omega_a}{dt} = \frac{K_t i_a}{J} - \frac{B}{J} \omega_a - \frac{T_L}{J} \tag{7}$$

As a linear time-invariant system, the aforementioned differential formulas are translated to a second-order state vector. The armature voltage and the DC motor's velocity are the 2 options. The applied voltage was the input, and the output represents the motor's velocity.
The state space description of the DC motor derived from (6) and (7) is as follows:

$$\dot{X} = AX + BU \tag{8}$$

$$\frac{d}{dt}\begin{bmatrix} i_a \\ \omega_a \end{bmatrix} = \begin{bmatrix} -\frac{R_a}{L_a} & -\frac{K_v}{L_a} \\ \frac{K_t}{J} & -\frac{B}{J} \end{bmatrix} \begin{bmatrix} i_a \\ \omega_a \end{bmatrix} + \begin{bmatrix} \frac{1}{L_a} \\ 0 \end{bmatrix} V_a \tag{9}$$

Where A is the system matrix and B is the input matrix.
If ω_a is selected as output, then the output equation is given by,

$$Y = CX \tag{10}$$

where $C = [0 \quad 1]$. The parameters of the DC motor is given in (**Table 1. Parameter of DC motor).**

Table 1. Parameter of DC motor

PARAMETER	SYMBOL	VALUE	UNIT
Armature resistance	R_a	2.06	Ω
Inductance	L_a	0.238	mH
Back EMF constant	K_v	0.02352	Volt-sec/rad
Torque costant	K_t	0.0235	Nm/A
Rotor inertia	J	$1.07e^{-6}$	$\mathrm{Kg}m^2$
Mechanical damping factor	B	$12e^{-7}$	No unit

2.2. Fault modelling

Different types of problems can occur in an electrical DC motor. The defects may harm the motor's internal structure or cause it to fail completely. The variation of the output when compared to the actual output owing to a change in parameter value can be used to discover faults. Bearing fault, short circuit fault, open circuit fault, and fault due to change in inertia are some of the issues that affect DC Motors. Fault modelling is

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accomplished by altering the values of parameters in the system matrix such that the parameter value changes by 50% from the constant value. Various fault models are

1. Bearing faults are widespread in electric motors, accounting for 40–50% of all motor failures. It occurs mostly due to the existence of friction, which can be produced by a variety of factors, including unanticipated overload, insufficient or inappropriate lubrication, faulty bearing installation, and so on. Internal friction increases as the mechanical damping factor exceeds the constant value. As a result, a bearing fault is simulated as a 50% increase in mechanical damping factor.
2. Another defect that impacts torque is the inertia fault. High-level machines can withstand higher load inertias, although some low-level machines are unable to do so. An increase in inertia will result in a reduction in acceleration. As a result, inertia fault is modelled as a 50% increase in rotor inertia.
3. • A short circuit defect occurs when the insulation between phase conductors, phase conductor(s) and earth, or both, fails. The resistance of a circuit is lowered, allowing a large quantity of applied voltage to flow. The system becomes overheated as the flow of huge current increases. As a result, a short circuit fault is represented as a 50% reduction in armature resistance.
4. An open circuit fault is any defect that causes a machine to stop working because of an open wire or component. The most common causes of these faults include joint failures of cables and overhead lines, failure of one or more phases of a circuit breaker, and melting of a fuse or conductor in one or more phases. As a result, a 50 percent rise in armature resistance represents an open circuit fault.

3. Methodology

3.1 Kalman filter

Kalman filter was an optimal estimator which helps to estimate past, present and future state behaviour of the system. A fault detection and identification strategy based on the Kalman filter is designed.The algorithm is recursive. The Kalman filter uses a dynamic model, measured control input and process measurement to estimate the process output. In DC motor, Kalman filter combines all measurement data along with previous state to estimate a desired output. It can be executed in real time, with only the current input observations and the previously computed condition and its uncertain matrix as inputs. To ensure quicker resolution, stochastic monitors such as the Kalman filter must be fine-tuned by choosing the right state distortion matrix and observation noise vector.

The continuous time state model is discretised and is given by,

$$X_k = FX_{k-1} + GU_k + w_k \tag{11}$$

Where X k represents the process's position vector at time k, F was the process's assumed static state transformation matrix, and 〖w〗 k represents the related white noise phase with known correlation Q.

$$Y_k = HX_k + v_k \tag{12}$$

Where Y k denotes the exact dimension of x at time k, H denotes the noiseless link between the state space and the measurement matrix (output matrix), which is considered to be stationary across time, and v k denotes the measured noise with correlation R.

For optimal separation efficiency, proper choice of the 'Q' and 'R' matrices is critical. The covariance vectors of the 2 noise types are supplied, and they are considered to be stationary throughout time.

$$Q = E[w_k w_k^T] \quad (13)$$

$$R = E[v_k v_k^T] \quad (14)$$

Kalman filter algorithm consists of two stages: prediction and correction. The first step in Kalman filter is prediction (time update). It contains prediction estimate and measurement update, in which the prediction estimate is calculated by assuming the initial states. The prediction estimate is given by,

$$\hat{X}_k = F\hat{X}_{k-1} + Gu_k + w_k \quad (15)$$

The prediction covariance is obtained by

$$P_k' = FP_{k-1}F^T + Q \quad (16)$$

The Kalman gain is the weighting given to observations and present state estimates, and it can be tweaked to produce a certain result.

It is possible to create an update formula for the new estimate by merging the previous estimate with measured data, presuming the prior estimate $\hat{X}_k{}'$. Thus,

$$\hat{X}_k = \hat{X}_k{}' - K(Y_k - H\hat{X}_k{}') \quad (17)$$

Where, K is the Kalman gain. $(Y_k - H\hat{X}_k{}')$ is known as the innovation or the measurement residual.

The Kalman gain can be determined by

$$K = P_k' H^T [P_k' H^T + R]^{-1} \quad (18)$$

The final step of Kalman filter is correction. It contains the steps namely error calculation, updated estimate and updated covariance. The Error calculation is done by subtracting the estimated output from the actual output,

$$E = Y_k - H\hat{X}_k \quad (19)$$

The Kalman gain, which is provided by, is used to derive the revised estimate and covariance.

$$\hat{X}_{k+1} = \hat{X}_k + KE \quad (20)$$

$$P_{k+1} = [I - KH]P_k \quad (21)$$

3.2 Internal model based Kalman filter

The design of the Kalman filter was established using a deterministic model employing the internal model concept, which defines the required and necessary condition for monitoring the outcome of a complex system. A Kalman gain was determined by minimising the correlation of the state prediction error to stabilise the filter, which contains a copy of the simulation environment driven by the regression. If the filter's stability is assured, the tracking loss will asymptotically disappear to zero for all changes in the Kalman gain using the internal modeling framework. The filter design in (**Figure 2. Structure of Internal model based Kalman filter**) includes the internal model, which is an exact replica of the model (F, G, H). The tracking error e drives the internal model (k).

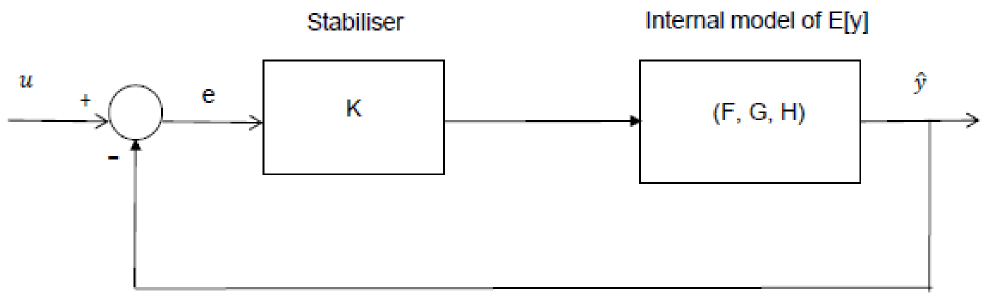

Figure 2. Structure of Internal model based Kalman filter

The resulting closed-loop system is then stabilized by the gain K which is suitably termed as the Kalman gain. Note here that finding the gain K is at the heart of Kalman filtering, regardless of the approach used to derive the filter's structure. The mathematical model of the Kalman filter becomes:

$$\hat{X}(k+1) = \hat{X}(k) + Gu(k) + K\left(Y - H\hat{X}(k)\right) \quad (22)$$

$$\hat{Y}(K) = H\hat{X}(k+1) \quad (23)$$

Where, is the Kalman gain which plays the role of a stabilizer. Subtracting the filter output model (22) from the system model (11) yields,

$$\tilde{X}(k+1) = (F - KH)\tilde{X}(k) + Kv(k) + Ew(k) \quad (24)$$

4. Results and Discussions

For the DC motor model, simulation studies were conducted using model-based state estimation techniques, Kalman filter, and Internal-model based Kalman filter for non-linear defect identification and diagnosis. The system is excited with a step input and the initial state is considered to be at the origin. A model-based filter actively monitors DC motor states for any irregularities in system response caused by faults. (**Figure 3. Open loop response**) depicts the DC motor's open loop response.

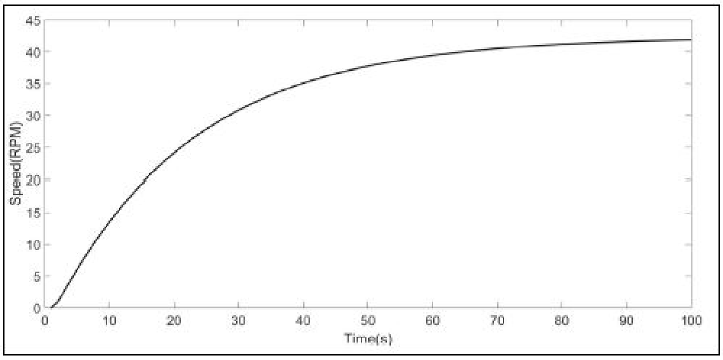

Figure 3. Open loop response

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The initial covariance for all possible cases is assumed to be $P = diag\{10\ 10\}$. The process and measurement noise covariance are assumed as $Q = diag\{0.01\ 0.01\}$ and $R = diag\{0.1\ \ 0.1\}$. The output of both actual and estimated system is plotted in the (**Figure 4. Normal model response using Kalman filter**). The error is defined as the difference between actual system and estimated system which is also shown in (**Figure 4. Normal model response using Kalman filter**).

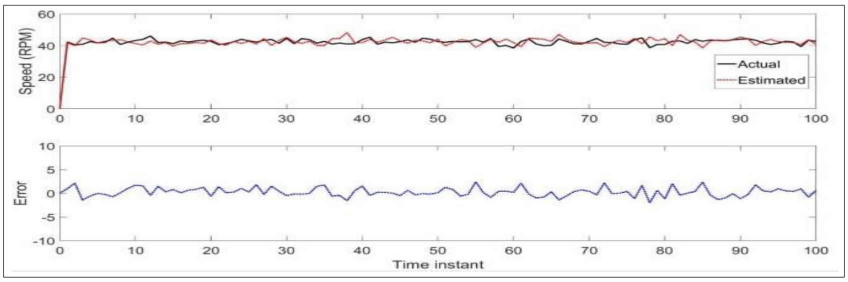

Figure 4. Normal model response using Kalman filter

The initial estimated state of Internal Model based Kalman filter is obtained by applying the value of Kalman gain derived from Kalman filter. The final estimated state is derived by calculating the state estimation error. Here also the output of actual and estimated system and their difference is plotted in the (**Figure 5. Normal model response using Internal model based Kalman filter**).

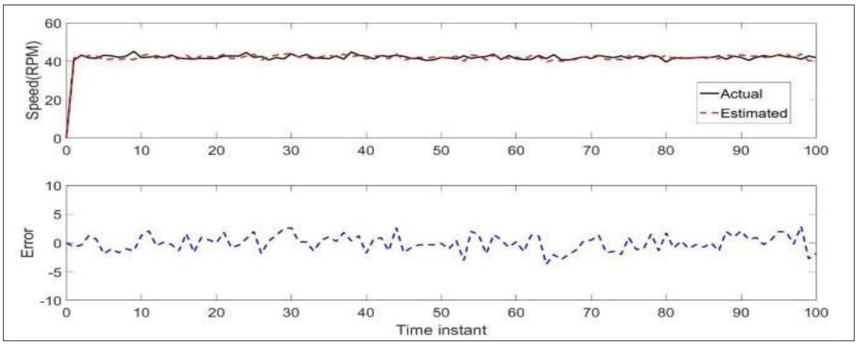

Figure 5. Normal model response using Internal model based Kalman filter

The four faults are bearing fault, fault due to inertia, short circuit fault and open circuit fault. For bearing fault the changes will occur in the parameter B. The mechanical damping factor B is changed because of friction created in the ball bearing of DC motor. It will leads to decrease in the speed of DC motor. (**Figure 6. System response with bearing fault**). Shows the system response under bearing fault.

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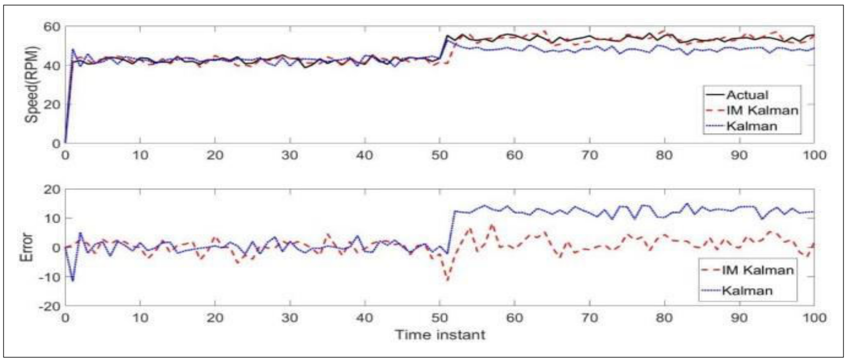

Figure 6. System response with bearing fault

In (**Figure 7. System response due to Inertia fault**), the changes occurred in the actual system is due to increase in the value of inertia. From the figure, the response for both Kalman and Internal Model based Kalman is observed.

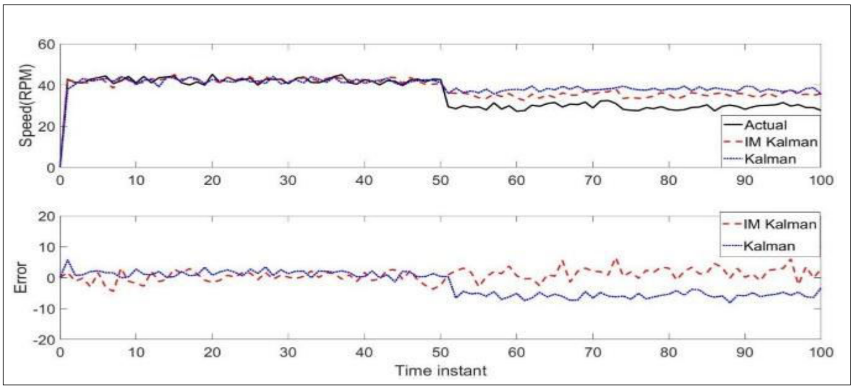

Figure 7. System response due to Inertia fault

For short circuit fault, the resistance in motor is reduced causing the input voltage flow in a large amount. Because of enormous flow of current, the speed of the motor will increase. This will be visualized in the (**Figure 8. System response with short circuit fault**).

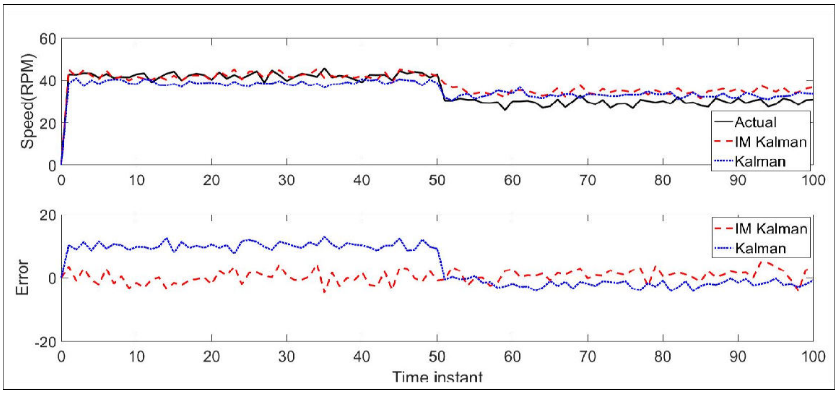

Figure 8. System response with short circuit fault

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For open circuit fault, the resistance in motor is increased, the current can't flow further. The continuous supply causes the increase in current at resistance which leads to breakage of the circuit. It results in gradual reduction of the speed of motor. Here, the speed decreases after the time instant of 50 which is shown in (**Figure 9. System response with open circuit fault**).

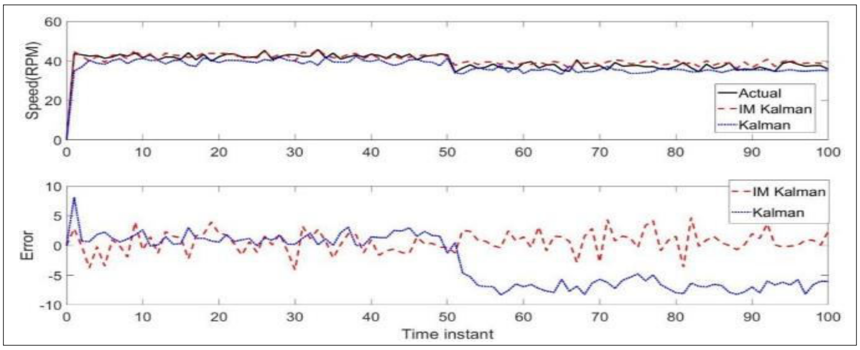

Figure 9. System response with open circuit fault

The performance of Kalman and IM based Kalman filter using Mean Squared Error (MSE), to find the accuracy of the estimated value. The Mean Squared Error is calculated by,

$$Mean = \sum_{k=0}^{t} (E)^2$$

The values of mean for all faults using Kalman and IM based Kalman filter are calculated and tabulated (**Table 2. Mean square error values**).

Table 2. Mean square error values

	KALMAN FILTER	IM BASED KF
Actual System	-0.4455	0.4059
Bearing Fault	-0.5941	0.2178
Fault due to inertia	-0.0792	0.1980
Short circuit fault	-0.3168	-0.1980
Open circuit fault	-0.3762	-0.0990

5. Conclusion

The model-based method is used to propose a defect identification and diagnosis technique for a DC motor model. A mathematical model is used to aggregate many parameter readings in real time, allowing for better fault identification. In the fault detection and diagnosis approach, the Kalman filter and the internal model based Kalman filter are used. A DC motor issue was effectively detected using the proposed method. Changing the value of the parameter by 50% from its constant rate to apply a continuous fault to the DC motor system. As a result, the proposed system is capable of detecting four different forms of DC motor faults: bearing failure, short circuit fault, open circuit fault, and inertia fault. The output response is presented in this project illustrate the effectiveness of the proposed methods.

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