A robust stator inter-turn fault detection in induction motor utilizing Kalman filter-based algorithm

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\textbf{Abstract}

Today, due to the widespread utilization of Induction Motors (IMs) in different industries, their condition monitoring is of great importance. Concentrating on the failures of IMs, it has been acknowledged that the stator inter-turn faults (SITFs) are the most frequent electrical failures. This paper puts forward an algorithm for SITF detection founded on Kalman Filter (KF). More specifically, the proposed algorithm employs KF to extract motor current signatures (MCS) and motor voltage signatures (MVS). Afterward, a statistical SITF index is used, based on the standard deviation of the extracted signatures. The proposed SITF index is technically robust against non-fault conditions including voltage quality problems and heavy load changes as well as having a significant performance in the presence of high measured noise-impregnated signals due to utilization of KF algorithm-based. Moreover, during source harmonic pollutions, the proposed algorithm has a very robust performance. Also, due to straightforward and low-computational mathematical basis, the proposed method is computationally efficient. The performance of the proposed method is validated with numerous simulation and experimental scenarios. The results indicate the proposed SITF index has robust performance, promising accuracy and good speed of convergence.

\textbf{Keywords:}
Induction motors (IMs)  
Stator inter-turn fault (SITF)  
Voltage quality problem  
Kalman filter (KF)

1. Introduction

Induction Motors (IMs) as electromechanical energy conversion devices because of lower cost, strong construction, high reliability, and wide range of speed have wider applications and critical role in industries. However, some failures may occur in them due to different mechanical, environmental, and electrical stresses [1]. Statistical reports on the failures of IM reveal that about 30\textperthousand–40\textperthousand of the electrical failures are related to the stator-winding and the rest are dedicated to the rotor [2]. The stator-winding faults may begin with Stator Inter-Turn Fault (SITF) and without immediate detection they can be led to more severe faults such as coil-to-coil, phase-to-phase, or phase-to-ground faults [3]. When SITF occurs between two turns, the voltage difference between these turns may overcome the insulating capacity and cause insulation breakdown in the motor stator-windings. Eventually, an arc and short circuit can be created in the entire coil. Therefore, detecting the SITF at an early stage is very crucial for monitoring the healthiness of the IMs.

For the detection of different stator-winding faults, numerous methods have been proposed, generally classified into model-based, signal-based, and artificial intelligence-based approaches [4].

According to Table 1, model-based methods are based on analytical models (fuzzy logic models [5], generic models using neural networks [6], and mathematical models) of the process to generate the normal outputs. The generated normal outputs of analytical models compare with the actual process outputs and generate residuals and faults are detected based on this residual signal. Due to this complexity, the accuracy of this model is usually not very good [7].

Compared to signal processing-based methods, they have insufficient accuracy and high complexity in fault detection [8]. Signal-based approaches can be broadly categorized into invasive and non-invasive methods [9]. Different tools can be used for extracting the harmonic components of signals in the frequency domain such as Fast Fourier Transform (FFT) [10], time domain such as correlation functions [11], and time–frequency domain such as Short Time Fourier Transform (STFT) [12], and Wavelet Transform (WT) [13]. Among these tools, FFT
is known as one of the most popular harmonic analyses for steady-state conditions that may experience notable inaccuracy during dynamic conditions. By mapping the signal in time and frequency domains, STFT can be utilized for both steady-state and dynamic conditions. However, STFT suffers from the utilization of a fixed-size window for analyzing all dynamics with different frequencies, accurately. To overcome the drawbacks of STFT, Wavelet Transform (WT) with a variable-sized window has been recommended as a time–frequency domain technique. Unfortunately, WT has a hypersensitivity to mounted noise on the signal and needs different sampling frequencies for different frequency sub-bands. Moreover, it has several other important shortcomings in analyzing the harmonic components such as different types of decomposition approach (DWT and WPT)-dependence on the number of levels and type of wavelet as well as its orders and method of approximating the analytical signal (via FFT or FIR). In this way, owing to the failure of FFT in dynamic conditions such as STFT and the mentioned drawbacks of the WT, it is suggested to utilizing the Kalman Filter as a suitable and efficient option to cover all the weaknesses of other techniques especially the ability to analyze the harmonic components of noise-impregnated signals.

In the invasive methods, the required signals of the algorithms are extracted by additional sensors which are needed physical connection with the electrical machine, and compared to non-invasive methods, they have less accuracy in fault detection. The signals used in this category include the following:

- Acoustic noise [14]: Generally, the noise spectrum of IM includes air conditioning noise and electromagnetic motive noise. Installed sensors may be mistaken for weak faults due to the influence of adjacent equipment [9].
- Stator frame vibration [15]: The main cause of vibration in the stator frame is the resonance between the electromagnetic force and the stator. The disadvantages of this index are low accuracy in the detection of weak faults and highly cost [9].
- Temperature [16]: Another quantity that changes when a STIF occurs is the winding temperature which can be detected by installing the sensor which must be electrically insulated. This index cannot detect weak faults and also has low reliability. Due to installation obstacles, temperature monitoring of the motor are only used in large machines [9].

As an overall trend, some of the disadvantages of the invasive methods compared to the non-invasive methods are low reliability, weak performance in fault detection, high cost, and disturbing normal operation due to sensor installation [9].

Many indicators can be used in non-invasive methods such as the air-gap torque [17], instantaneous electrical power [18], negative sequence of stator currents [19], stator current zero-crossings [19], instantaneous frequency [20], instantaneous total harmonic distortions (ITHDs) [21] indicators have maloperation in distinguishing between faulty and other conditions such as voltage sag and voltage swell problems.

Some other methods for the detection are based on artificial intelligence like fuzzy logic [24], evolutionary algorithms [25], and artificial neural networks [26]. There are two main drawbacks in this category including the need for a massive dataset for the training and the inability of self-learning without feature extraction. Although the methods based on deep learning [27] have addressed this shortcoming, however, they still require a huge dataset.

According to Table 1, it can be comprehensively inferred that the model-based methods have low accuracy and the signal-based (invasive) ones due to the installed sensors cannot detect weak faults well. To overcome the problems of this category, it is recommended to use signal-based methods (non-invasive). One of the most important disadvantages of methods based on artificial intelligence is their highly computational burden. As an overall trend, the proposed method which is one of the signal-based (non-invasive) category is able to eliminate the disadvantages of the other methods and show much higher accuracy.

<table>
<thead>
<tr>
<th>Method</th>
<th>Speed</th>
<th>Accuracy</th>
<th>Computational Burden</th>
<th>Need to additional sensor installation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-based</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>No</td>
</tr>
<tr>
<td>Signal-based invasive</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Yes</td>
</tr>
<tr>
<td>Signal-based non-invasive</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>No</td>
</tr>
<tr>
<td>Artificial intelligence-based</td>
<td>High</td>
<td>High</td>
<td>Very High</td>
<td>No</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Very High</td>
<td>Very High</td>
<td>Low</td>
<td>No</td>
</tr>
</tbody>
</table>

Table 1
A qualitative comparison between different groups and the proposed method.
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1. Robustness to non-fault conditions including voltage quality problems (voltage sag, voltage swell, unbalanced voltage, voltage fluctuation due to capacitor switching and parallel motor switching) and heavy mechanical load changes.
2. Straightforward and low computational mathematical.
3. Capable of detecting the inter-turn faults in the presence of source harmonic contaminations.
4. Significant ability to detect faults in the presence of Gaussian noise.
5. No need for installing an additional sensor.
6. Having high accuracy and speed.

The rest of the paper is organized as follows: In Section 2, a mathematical model of the IMs considering STIF and fault resistance \( R_f \) is presented. Section 3 describes the structure and process of KF and as well as the proposed method in more detail. The validation of the proposed method using simulation data is verified in Section 4. In Section 5, the performance of the proposed indices with experimental data is investigated. In Section 6, the effect of some important parameters on the proposed index will be discussed and Section 7 fairly compares the performance of the proposed method with other similar methods. Section 8 provides the conclusion of this paper.

2. Mathematical model of induction motor with SITF

Introducing a model of IMs is an important subject to illustrate the variables changes in different motor operating conditions and to verify the performance of fault diagnosis approaches. Hence, in recent decades, a large number of models for IMs have been proposed [28]. In this research, a \( qd0 \) model by adding fault resistance \( R_f \) and some minor changes is presented [29].

It should be noted that this model is based on the following assumptions [30]:

- The temperature of the motor stays constant. In this way, the parameters of the motor do not change.
- The magnetic field is not saturated and it also has a constant permeability.
- The notching effects and generating space harmonic can be ignored due to the thickness of the air gap is assumed to be constant.
- The hysteresis, skin, and eddy effects are not considered.
- The magneto-motive forces generated by the stator and rotor phases propagate sinusoidally along the air gap.

According to Fig. 1, the equations for the stator and rotor circuit of IMs in SITF condition are written as follows:

\[
V_{ab,c} = [R_s]_{ab,c} \frac{d}{dt} \psi_{ab,c} - Z_s I_f
\]

\[0 = [R_s]_{ab,c} \frac{d}{dt} \psi_{ab,c} - Z_s I_f \]

\[R_f I_f = \beta R_s I_{sd} - \beta R_f I_f + \frac{1}{\omega_0} \frac{d}{dt} \psi_{ab,c} \]

where \( V_{ab,c}, I_{ab,c}, \psi_{ab,c} \) and \( \beta \) are three-phase voltage, three-phase current, three-phase flux linkage per second, and the ratio of the shorted turns to the total number of turns in one phase, respectively. Also, \( [R_s] = \text{diag}[R_sR_sR_s], [R_f] = \text{diag}[R_fR_fR_f], Z_s = [\beta R_s 0 0]^T \). It should be noted that the subscripts of \( s, r \) and \( f \) are related to the stator, rotor, and fault, respectively.

The flux linkages (per second) of (1)–(3) are calculated as follows:

\[
\psi_{ab,c} = [X_s]_{ab,c} I_{ab,c} + [X_s]_{ab,c} I_{ab,c} - [X_f] I_f
\]

\[
\psi_{ab,c} = [X_s]^T I_{ab,c} + [X_r]_{ab,c} - [X_f] I_f
\]

\[
\psi_f = [X_r]^T I_{ab,c} + [X_f]^T I_{ab,c} - X_f I_f
\]

where \( [X_s], [X_r] \) and \( [X_f] \) are matrices including the stator and rotor self reactances and their mutual reactance, respectively. Also, \( [X_f], [X_f] \) and \( X_f \) are vectors of the mutual reactance of stator winding and the faulty turns, mutual reactance of the rotor winding, as well as the faulty turns and self-reactance of the faulted turns, respectively.

The transient speed \( \omega_f \) and electromagnetic torque \( T_e \) are as follows:

\[
\frac{d}{dt} \omega_f = P \frac{T_e - T_l}{2J}
\]

\[
T_e = P \frac{1}{2 \omega_f} \frac{d}{dt} \psi_{ab,c} - P \frac{1}{2 \omega_f} \frac{d}{dt} [X_f] I_{ab,c}
\]

where \( T_l \) is the load torque, \( J \) rotor inertia and \( P \) is the number of poles.

By applying (9) to (1)–(8), voltage, current, and flux linkage equations will be as follows:

\[
K_r = \begin{bmatrix}
\cos(\theta) & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\
\sin(\theta) & \sin\left(\theta - \frac{2\pi}{3}\right) & \sin\left(\theta + \frac{2\pi}{3}\right) \\
-\frac{1}{2} & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}
\]

\[
V_{ab,c} = K_r^{-1} \omega_{ab,c}
\]

\[I_{ab,c} = K_r^{-1} \psi_{ab,c} \]

\[\psi_{ab,c} = K_r^{-1} \omega_{ab,c} \]

\[I_{ab,c} = K_r^{-1} \psi_{ab,c} \]

\[\psi_{ab,c} = K_r^{-1} \omega_{ab,c} \]

\[
V_{ab,c} = [R_s]_{ab,c} \frac{d}{dt} \psi_{ab,c} - K_s[Z_s] I_f
\]
3. The suggested method for SITF detection in IMs

In general, when STIF occurs, in addition to the fundamental component, the following components appear in the air–gap flux density, consequently, these components are induced in the stator current [31].

\[ f_{STIF} = \frac{p}{2} (1 - s) + k \]

where \( f_{STIF} \), \( p \), and \( k \) denote the fundamental frequency, the number of pole pair, motor slip, and SITF components relevant to the shorted of order \( n = 1, 2, 3, \ldots \) respectively. Also, \( k = 1, 3, 5, \ldots \) is the order of stator time harmonics.

To investigate the behavior of the SITF components, the fundamental component must be separated from the other components. Therefore, in the proposed approach, a slow dynamic KF is employed for estimating the frequency components of the stator voltage and current signals.
component to detect the SITF. In the following, the KF formulations for the
fundamental component are described.

Fig. 3. The implementation procedure of the proposed SITF index.

Afterward, the residual signals are calculated using the difference be-
tween the stator measured signals and the estimated fundamental
condition for selecting a threshold value of voltage index.

Fig. 4. The threshold selection process using Otsu thresholding method. (a) PDF curves of normal condition and fault condition for selecting a threshold value of current index (b) PDF curves of voltage quality problem and fault condition for selecting a threshold value of voltage index.

3.1. Kalman filter structure and process in the fundamental component estimation

To construct the structure of KF, a mathematical model of signal in
state space is required. The stator signals of the IMs may change under
different conditions such as SITF, load changes, and power quality
problems. In this way, it can be assumed to include some frequency
components as follows:

\[ x(t) = \sum_{n=1}^{N} A_n \cos(o_n t + \varphi_n) + \mu_t \]  

where \( x \) is stator measured signals, \( A \) is the amplitude of the signal, \( N \) is harmonic order, \( o_n = 2\pi f_n \) is the angular frequency of harmonic \( n \)th as well as \( f_0 \) is the fundamental frequency. Also, parameters \( \varphi_n \) and \( \mu_t \) represent the phase of harmonic \( n \)th and random noise, respectively. Equation (24) can be rewritten in discrete form as follows:

\[ s_m = A_n \cos(o_n m T_s + \varphi_n) + \mu_n \]  

(25)

where parameters \( T_s \) and \( m \) are the sampling period and number of each sample.

To define the states of KF, a recursive relationship based on trigo-
nometric identities as follows:

\[ S_{e(m+1)} + \mu s_{mn} = 2 \cos(o_n T_s) + \mu s_{mn} \]  

(26)

where \( \mu s_{mn} \) represent the possible model error with zero average which includes slight amplitude, phase, or frequency deviations. It should be considered that the measured signal might be affected by noise or other disturbing factors. So:

\[ V_n = x_m + \mu_s \]  

(27)

In order to estimate the fundamental component of a signal with the
Kalman filter, it is necessary to write the equations in the state space
form by using the Eqs. (26) and (27), which is as follows:

\[ X_{e(m+1)} = M_n X_{mn} + b \mu s_{mn} \]

\[ V_n = h^T X_{mn} + \mu_n \]  

(28)

where

\[ X_{mn} = [S_{mn} S_{mn-1}]^T, \ M_n = \left[ \begin{array}{c|c} 2 \cos(o_n T_s) & -1 \\ \hline 1 & 0 \end{array} \right], b = [1 \ 0]^T \text{ and } h = [1 \ 0]^T. \]

According to the equations mentioned above, a classical iterative KF
based on the following algorithm has been used to estimate the funda-
mental component of the signal and its algorithm is shown in the flowchart form in Fig. 2.

i. Initial estimation for state vector and its error covariance (\( \vec{X}_{mn} \) and \( P_{mn} \))

ii. Compute the Kalman Filter gain at the sample time \( m \): \( K_n = (P_m h T / (h^T P_m h + \nu_m)) \)

iii. Update the estimate with measurement \( \vec{X}_{mn} = \vec{X}_{mn} + K_n (V_n - h T \vec{X}_{mn}^{-1}) \) where \( q_n = E(w_n^2), \ r_n = E(\mu_n^2), \ \vec{X}_{mn} = \bar{E}(X_{mn} | V_{k-1}, \ldots, V_1) \) and \( \vec{X}_{mn}^{-1} = \bar{E}(X_{mn} | V_k, \ldots, V_1) \) are priori estimate of state vector \( X_{mn} \) at the sample time \( m \) using the observation \( V_1 \) to \( V_{k-1} \) and posterior estimate of this state vector after using thenth observation \( V_k \), respectively.

iv. Update the error covarance using \( P_{mn} = P_{mn} - K_n h T P_{mn} \) where, \( P_{mn} \) and \( P_{mn} \) are Priori and Posteriiori error covarance matrices, respectively.

v. Project the state ahead: \( \vec{X}_{n(m+1)} = M_n \vec{X}_{mn} \bar{P}_{n(m+1)} = M_n P_{mn} M_n^T + b q_n b^T \)

vi. Return to 2

In general, there are two main parameters in KF which determine the
dynamic response and accuracy of the filter. These parameters are sta-
tionary process model (\( q_n = q \) ) and stationary observation (\( r_m = r \)). In
order to estimate the fundamental component of signals with desirable

Fig. 5. Actual and estimated fundamental component of the current signal.
speed and accuracy, the values and the ratio of these two parameters must be adjusted.

3.2. Implementation of the proposed algorithm

When an STIF occurs, many physical and electrical quantities such as stator current components change. In this situation, just the fundamental component of the current does not indicate the signatures of the fault, because some other conditions like load growth may have the same signatures. Therefore, the signatures of the other components should be considered. The main focus of the proposed algorithm is on all the components of the current except the fundamental. So, at the onset, the fundamental component of the current is estimated using the Kalman filter and according to Eqs. (29) and (30) it is subtracted from the original signal and it is considered as a residual signal of current.

Table 3
KF performance evaluation for different values of \( q \) and \( r \).

<table>
<thead>
<tr>
<th>( q )</th>
<th>( r )</th>
<th>Mean Square Error (MSE)</th>
<th>Delay (s)</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 10^{-1} )</td>
<td>( 10^{-1} )</td>
<td>0.776</td>
<td>0.0865</td>
<td>Poor</td>
</tr>
<tr>
<td>( 10^{-2} )</td>
<td>( 10^{-1} )</td>
<td>0.536</td>
<td>0.0651</td>
<td>Good</td>
</tr>
<tr>
<td>( 10^{-3} )</td>
<td>( 10^{-1} )</td>
<td>0.391</td>
<td>0.0467</td>
<td>Good</td>
</tr>
<tr>
<td>( 10^{-4} )</td>
<td>( 10^{-1} )</td>
<td>0.201</td>
<td>0.0125</td>
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<tr>
<td>( 10^{-5} )</td>
<td>( 10^{-1} )</td>
<td>0.097</td>
<td>0.0258</td>
<td>Very Good</td>
</tr>
<tr>
<td>( 10^{-6} )</td>
<td>( 10^{-1} )</td>
<td>0.038</td>
<td>0.0368</td>
<td>Very Good</td>
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<tr>
<td>( 10^{-1} )</td>
<td>( 10^{-2} )</td>
<td>0.941</td>
<td>0.1047</td>
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<td>( 10^{-2} )</td>
<td>( 10^{-2} )</td>
<td>0.516</td>
<td>0.0843</td>
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</tr>
<tr>
<td>( 10^{-3} )</td>
<td>( 10^{-2} )</td>
<td>0.286</td>
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<tr>
<td>( 10^{-4} )</td>
<td>( 10^{-2} )</td>
<td>0.142</td>
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<td>( 10^{-5} )</td>
<td>( 10^{-2} )</td>
<td>0.107</td>
<td>0.0102</td>
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<tr>
<td>( 10^{-6} )</td>
<td>( 10^{-2} )</td>
<td>0.086</td>
<td>0.0236</td>
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<tr>
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<td>1.056</td>
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<td>( 10^{-2} )</td>
<td>( 10^{-3} )</td>
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<td>0.0621</td>
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<td>( 10^{-5} )</td>
<td>( 10^{-3} )</td>
<td>0.115</td>
<td>0.0414</td>
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<tr>
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<tr>
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<td>0.0611</td>
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</tr>
<tr>
<td>( 10^{-6} )</td>
<td>( 10^{-4} )</td>
<td>0.107</td>
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</tr>
<tr>
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<td>( 10^{-5} )</td>
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<td>( 10^{-5} )</td>
<td>0.162</td>
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<td>( 10^{-6} )</td>
<td>( 10^{-6} )</td>
<td>0.252</td>
<td>0.0974</td>
<td>Good</td>
</tr>
</tbody>
</table>
where \( r_v \) and \( r_i \) are residual signals of stator voltage and current, respectively. Also, \( v_s \) and \( v_{50Hz} \) represent the measured phase stator voltage and its fundamental component which are estimated by KF as well as \( i_s \) and \( i_{50Hz} \) are defined similarly. At the final step, the standard deviation of the residual signals is introduced as fault detection index according to the following equation:

\[
\sigma_j = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x_{ij} - \mu_j)^2}
\]

where \( \sigma_j \), \( N \), \( x_{ij} \) and \( \mu_j \) denote the standard deviation of \( j \)-th window of data, the number of window’s samples, \( i \)-th sample of of \( j \)-th window of data and the mean value corresponding to \( j \)-th window of data respectively.

It should be noted that in the other conditions such as voltage quality problems, the performance of the index is similar to the faulty condition, hence, to prevent this maloperation, the stator voltage and the standard deviation of its residual signal are utilized as input to the algorithm and auxiliary index, respectively.

Moreover, to complete this algorithm, it is necessary to define two thresholds for voltage and current indices which should be selected based on simulation and experimental results in different conditions. When a fault occurs, the current index exceeds its threshold value and the voltage index is less than its threshold value at the same time whereas if both of the voltage and current indices exceed their defined thresholds, this can be considered as voltage quality problems. If none of the above scenarios occur, the motor is in normal operating condition. The flowchart of this algorithm is presented in Fig. 3.

4. The performance evaluation using some simulations

In this paper, to investigate the dynamic fault behavior, a threephase IM with 0.75KW, 220 V, 4 poles and 50 Hz is simulated according to the Eqs. (15) to (22) in MATLAB/SIMULINK. The specifications of the scenarios are provided in Table 2.

According to Fig. 3, the stator currents and voltages of the motor were captured from the simulink with a sampling time of 128 μs. Afterward, a sliding data window with a length of 156 samples equivalent to one cycle (20 ms) is utilized for the data analysis. The window is updated cycle by cycle and the fundamental components of the stator current and voltage corresponding to each window are extracted via a KF with \( q = 10^{-6} \) and \( r = 10^{-3} \). Finally, the standard deviation of the residual signals is calculated. It should be noted that the threshold values for \( Th_i \) and \( Th_v \) are selected 0.02 and 0.03, respectively based on Otsu thresholding method [32] in 450 simulation cases and 50 practical cases including inter-turn fault, voltage quality problems, and mechanical load growth.

The implemented process of Otsu thresholding method includes three main steps as follows.

1. A probability function density (PDF) is assigned to each of the current and voltage indices in each scenario.
2. A curve with a normal Gaussian function is fitted to each scenario.
3. The intersection point of the two PDF curves in the desired scenarios is selected as the threshold.

As seen in Fig. 4(a), the PDF curves of normal condition and fault condition have an intersection point in 0.02. Therefore, \( Th_i = 0.02 \) is a suitable value threshold in the current index for discriminating inter-turn fault from the normal condition. Moreover, according to the simulation and practical results, the performance of the current index is
similar to voltage quality problems. To prevent this malfunction, the voltage index is utilized as an auxiliary index. In fault conditions, the voltage and its corresponding index have slight changes as normal condition whereas, in voltage quality problem cases, the voltage index changes significantly. Therefore, Otsu thresholding method has been used to differentiate the fault criterion changes from voltage quality problems by selecting an appropriate threshold. According to Fig. 4 (b), $T_{th} = 0.03$ can be an appropriate value threshold in voltage index for having a robustness performance against the voltage quality problems.

In KF, there are two main parameters which the dynamic response and accuracy of the KF are dependent to them. These parameters are measurement noise covariance ($r$) and process noise covariance ($q$) which includes slight amplitude, phase, or frequency deviations. It should be noted that the values of these two parameters determine the accuracy of the estimated states by KF and also the ratio of these two parameters affects the KF delay.

The delay in the KF means how long does it take that estimated state by the KF follows the measurement signal. As shown in Fig. 5, the black signal is the stator current with the fundamental frequency and the red signal denotes the estimated signal of the fundamental component by the KF. The red signal follows the black after half a cycle (0.01 s) and after that the difference between the two signals reaches an acceptable value. So, here the delay is 0.01 s.

The accuracy of the KF is determined by (32) which represents the Mean Square Error (MSE).

$$MSE_j = \frac{1}{N} \sum_{i=1}^{N} (i_{as} - s_{est})^2$$  \hspace{1cm} (32)

where $MSE_j$, $N$, $i_{as}$ and $s_{est}$ denote the Mean Square Error of $j$-th window of data, the number of window's samples, stator current (observed value) and estimated fundamental component (estimated value), respectively.

To evaluate the performance of KF, the MSE and delay for values $10^{-1}$ to $10^{-6}$ of $q$ and $r$ as the typical covariance values are calculated and the results are provided in Table 3.

To select the suitable value for $q$ and $r$, a tradeoff must always should be performed between the minimum delay and MSE. In this way, considering Table 3, $q$ equals $10^{-6}$ and $r$ equals $10^{-3}$ has the lowest delay (about 0.01 s) and also the appropriate MSE about of 0.05 compared to the other cases. It should be noted that although in other cases such as $q$ equals $10^{-6}$ and $r$ equals $10^{-1}$, the MSE is 0.038 and has a lower value than 0.053, but its delay is more than 0.0096. As an overall trend, the selection of $q$ equals $10^{-6}$ and $r$ equals $10^{-3}$ can be suggested as a suitable tradeoff among the selected parameters of the KF.

### 4.1. Fault scenarios

This section investigates the behavior of the proposed index in the case of internal faults in the stator of the IM. Considering $\beta$ as the severity of the fault, several fault scenarios for $\beta$ between 0.02 and 0.1 have been generated. Here, a typical inter-turn fault ($\beta = 0.05$) is presented for presenting the method in more detail. The stator current and voltage of phase A, their corresponding residual signals, and the proposed indices are illustrated in Fig. 6. As shown in Fig. 6(a), a minor fault was applied in the phase A of the stator winding. By calculating the residual signal, it can be observed in Fig. 6(b) that the distortions of the fault current signals lead to creating some errors in the estimation and as a result, the proposed index exceeds the threshold 0.02. On the other side of the algorithm, when a SITF occurs, the voltage signal changes slightly and the standard deviation of its residual signal changes from 0 to 0.001, but its value is less than 0.03 according to Fig. 6(d)-(f).
In practice, the voltage supply may be contaminated with high-order harmonic components. Obviously, some unwanted harmonic components result in distortions in the MCS and MVS even before the fault inception. Since the proposed index is designed based on the measuring distortions of the signals after disturbance inception, several case studies were conducted to investigate the ability of the proposed algorithm in presence of voltage supply contaminated with unwanted harmonic components. Different level of total harmonic distortions THDs between 1% and 5% was fed to the voltage supply. In the following, the performance of the algorithm is studied to detect the coil-to-coil fault ($\beta = 0.1$) considering 5% THD in the voltage supply. As shown in Fig. 7, at the moments before $t = 1s$, the residual signals of voltage and current are not zero due to harmonic contamination in the voltage supply and have a value and the current and voltage indices change from zero to 0.017 and 0.008, respectively, which are very close to 0.02 and 0.03. The results in Fig. 7 indicate that with the selected threshold, the proposed method is able to deal with unwanted harmonic components in voltage supply up to THD = 5%. It is worth mentioning that the higher-order level of harmonics can be dealt with using re-adjusting the thresholds.

Another challenge in STTF detection should be investigated is when the fault signal is intermittent. In IMs, the electromagnetic efforts are proportional to the square of the current passing through the winding-based Laplace forces equation. In such a way, the intermittent fault such as arcing fault in IM has the most possible when the stator current is near its peak value. Generally, an intermittent fault between the turns of one phase is modeled with variable resistance. This fault resistance ($R_f$) has small value when an inter-turn short circuit happens and allows current to flow between the shorted turns whereas in the absence of an inter-turn short circuit, the fault resistance value is very high. It should be note that the value of fault resistance depends on the insulation damage degree [33].

The results of intermittent are provided in Fig. 8. As seen in Fig. 8 (a), two 1-turn short circuits occur at negative and positive current peaks respectively and the current index at 0.998 s and 1.08 s exceeds 0.02. Moreover, the voltage index has the same performance of permanent STTF as previously discussed, which is less than its defined threshold value (0.03) when an inter-turn short circuit occurs.

### 4.2. Voltage quality problems

Non-fault transient conditions profoundly affect the performance of IMs. As a result, it is mandatory to investigate the performance of the proposed index under the most frequent transient conditions that may create ambiguity to inter-turn fault conditions. In the following, the performance of the proposed index under voltage sag and voltage swell are investigated. Figs. 9 and 10 represent the simulation results for voltage sag 20% and voltage swell 10%.

In Fig. 9, it can be seen that in a time interval of $t = 1s$ to $t = 1.1s$, a voltage sag 20% has happened and according to Fig. 9 (d) voltage of A-phase is changed from 1p.u to 0.8p.u. Moreover, the current index due to voltage sag increases noticeably by about 0.4 in Fig. 9 (c) and as shown in Fig. 9(f), there is a growth of about 0.08 in the voltage index. Hence, both the current and voltage index values exceed 0.02 and 0.03, consequently a voltage quality problem is detected.

Similar results for a voltage swell 10% can be seen in Fig. 10. As it can be observed in Fig. 10, a voltage swell 10% for 5 cycles has happened and based on Fig. 10(d), the voltage of A-phase is changed from 1p.u to 1.1 p.u. Also, Fig. 10(c) and Fig. 10(f) represent the considerable increases of 0.23 and 0.05 units in the current and voltage indices, respectively. Therefore, the proposed algorithm robustly discriminates such conditions from inter-turn faults in IMs.

Another possible voltage quality problem is imbalance voltage in supply. To study such a condition, an unbalanced supply voltage of 2.64% is studied and the simulation results are shown in the Fig. 11. It
Fig. 9. Performance of the proposed indices based on simulation result for a voltage sag 20%, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (e) the voltage index.

Fig. 10. Performance of the proposed indices based on simulation result for a voltage swell 10%, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (e) the voltage index.
should be noted that in this condition, the stator voltage of phases A, B, and C change from 1 p.u to 1.02 p.u, 0.98 p.u, and 0.98 p.u. Also, the voltage imbalance is expressed based on the following equation [34]:

\[
\text{Voltage imbalance} = \frac{\text{maximum deviation from average phase voltage}}{\text{average phase voltage}} \times 100 \tag{33}
\]

As the three-phase stator voltages are shown in Fig. 11(a), an unbalanced voltage occurs which results in an increase in three-phase voltage indices from zero to 0.07, 0.048, and 0.046 respectively which all of them are greater than 0.03. Furthermore, according to Fig. 11(c) and Fig. 11(d), the three-phase current has also changed and their corresponding indices increase from zero to 0.041, 0.043, and 0.058 respectively and the index values exceed 0.02. As a general trend, it can be argued when a voltage quality problem happens, both the current and voltage indices exceed their defined threshold values.

To complete the study of possible scenarios, the performance of the proposed indices in the capacitor switching and parallel motor switching scenarios have been investigated and their results are shown in Figs. 12 and 13.

As presented in Fig. 12(a), Due to a capacitor switching with increasing the power factor from 0.74 to 1, the current of the A-phase has a slight transient oscillation and its residual signal changes in Fig. 12(b) as a result of these oscillations and consequently, the current index exceeds 0.02 for 5 cycles in Fig. 12(c). On the other hand, while these transient oscillations occur as shown in Fig. 12(d), the residual voltage undergoes a sudden jump and the voltage index exceeds 0.03 for one cycle in Fig. 12(f). As a general trend, both current and voltage indices
Fig. 12. Performance of the proposed indices based on simulation result for a capacitor switching with increasing the power factor from 0.74 to 1, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (f) the voltage index.

Fig. 13. Performance of the proposed indices based on simulation result for a parallel motor switching, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (f) the voltage index.
Fig. 14. Performance of the proposed indices based on simulation result for a load change 80%, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (e) the voltage index.

Fig. 15. Experimental setup for detection of inter-turn fault.
Table 4
IM parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output power</td>
<td>750 W</td>
</tr>
<tr>
<td>Rated voltage</td>
<td>220 V</td>
</tr>
<tr>
<td>Rated current</td>
<td>3.6 A</td>
</tr>
<tr>
<td>Rated frequency</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Rated power factor cos(θ)</td>
<td>0.76</td>
</tr>
<tr>
<td>Rotor inertia</td>
<td>0.0025 Kg m²</td>
</tr>
<tr>
<td>Number of poles</td>
<td>4</td>
</tr>
<tr>
<td>No load speed</td>
<td>1385 RPM</td>
</tr>
<tr>
<td>Stator winding resistance Rs</td>
<td>8.4 Ω</td>
</tr>
<tr>
<td>Referred rotor winding resistance Rr</td>
<td>8.2 Ω</td>
</tr>
<tr>
<td>Stator winding leakage reactance Xr</td>
<td>10.3 Ω</td>
</tr>
<tr>
<td>Referred rotor winding leakage reactance Xr</td>
<td>10.3 Ω</td>
</tr>
<tr>
<td>Magnetizing reactance Xm</td>
<td>137.5 Ω</td>
</tr>
</tbody>
</table>

Fig. 16. Performance of the proposed indices based on the experimental result for an inter-turn fault (β = 0.05), (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (f) the voltage index.

exceed their defined thresholds.

The results of similar probabilistic transient oscillations are illustrated in Fig. 13. As presented in Fig. 13(a), parallel motor switching happens at t = 1 s and current decreased from 1 p.u to 0.95 p.u. Moreover, due to the occurrence of this switching, the current criterion has increased approximately from 0 to 0.025 in Fig. 13(c).

Furthermore, when this switching occurs, the voltage changes from 1 p.u to 0.95 p.u in Fig. 13(d), and consequently, a growth of about 0.045 in the voltage criterion happens Fig. 13(f).

4.3. Mechanical load growth

This section is dedicated to investigating the performance of the proposed index under a load change. A load growth of 80% is investigated in Fig. 14. As observed, although the stator current had significant changes from 1 p.u to 1.1 p.u and consequently, the current and voltage residual signals change according to Fig. 18(b) and Fig. 18(c). Hence, the current index value increased from 0.0136 to 0.14 and the voltage index value change from 0.021 to 0.058. Both the indices exceed their thresholds, so, it is recognized as a voltage quality problem.

Another voltage quality problem as an unbalanced voltage of 2.8% is studied in Fig. 19. This voltage imbalance has happened at t = 0.6 s and based on Fig. 19(a), the stator voltage of phases a, b and c changed from 1 p.u to 1.03 p.u, 0.95 p.u, and 0.95 p.u. As a result of this imbalance, in Fig. 19(b) the voltage index values have reached 0.032, 0.033, and 0.37 which all three index values are greater than 0.03. Furthermore, the three-phase currents also change and their corresponding indices have increased from 0.014 to 0.027, 0.029 and 0.046 respectively in Fig. 19(d).

To complete the study of the possible scenarios, the performance of the proposed index under a load growth is investigated by the experimental results in Fig. 20. In this case, the A-phase current increases from 1 p.u to 2 p.u according to Fig. 20(a) and consequently the current index value change from 0.01 to 0.016 which is less than 0.02. Moreover, no significant changes in voltage of A-phase is observed in Fig. 20(d). Hence, the value of the voltage index remains approximately equal to 0.02. As a general trend, both the current and voltage index values are less than their corresponding thresholds and this case can be considered as a normal operating condition.

6. Effects of different parameters on the proposed index

This section evaluates the flexibility of the algorithm considering the effects of different parameters including fault resistance, harmonic contamination in the supply voltage, load growth rate, and noise effect.

6.1. Effect of fault resistance

In this case, the fault resistance is changed from zero to 300 ohms for different β are investigated and the results are shown in Table 5.

The results of Table 5 are reported based on 450 different simulation cases and 50 different experimental cases. As shown in Table 5, the current index values of an inter-turn fault (β = 0.02) in fault resistance ranges between 0 and 1 are almost constant and have a value equal to 0.096. But, in case of a high value of fault resistance (Rf = 1000Ω), the index value decreases to 0.0701. The investigations are performed for the other fault intensities such as inter-turn faults from β = 0.005 to β = 0.07 and a coil-to-coil fault (β = 0.1). As can be seen, when one of the stator winding’s 144 turns is shorted, the value of the current index from fault resistance 0 to 1 ohm is approximately 0.032 and at very high fault resistance (Rf = 1000Ω), the value of the current index is 0.0245 which is
Fig. 17. Performance of the proposed indices based on the experimental result for voltage sag 20%, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (f) the voltage index.

Fig. 18. Performance of the proposed indices based on the experimental result for voltage swell 10%, (a) actual and estimated fundamental component of the current signal, (b) current residual signal, (c) the current index, (d) actual and estimated fundamental component of the voltage signal, (e) voltage residual signal, (f) the voltage index.
very close to the defined threshold (0.02). In this way, it is very important to evaluate the sensitivity of the proposed method to short circuit with an fault severity of less than 0.007.

According to the Table 5, in the fault severity of 0.01 and fault resistance value of 200 ohm, the current index value is very close to 0.02 and eventually at fault resistance resistance 300 ohm, the value of the current index doesn’t reach to 0.02. Furthermore, in the fault severity of 0.01 per fault resistance values of 200 and 300 ohm, the current index is less than 0.02 and the suggested method is not able to detect such this fault. As an overall trend, the detection limit of the proposed method is selected 1 short-circuited turn ($$\beta = 0.007$$) and fault resistance value of 100 so that the algorithm does not malfunction for different values of fault resistances.

Moreover, the value of the current index in each fault resistance increases with increasing fault intensity. For instance, as $$\beta$$ increases, the current index enhances from 0.0931 to 0.1391 for fault resistance 1Ω. As a result, the proposed algorithm has a robust performance for different fault resistance considering different fault intensities.

6.2. Harmonic contamination in supply voltage

As mentioned before, under normal conditions, both the current and voltage indices are less than their corresponding threshold. For detection of a fault condition, it is only sufficient to have the current index greater than 0.02 and the voltage index less than 0.03. However, if the voltage supply has severe harmonic contamination, the value of the current index before the fault occurrence moment may exceed 0.02 and also the voltage index value after the fault occurrence moment may exceed 0.03 which causes the malfunctioning in the proposed method. Therefore, the harmonic contamination is acceptable if it does not lead to maloperation in the proposed index. The results of this case are presented in Table 6. It should be noted that $$\Delta_i$$ is the distance between of threshold and current index before the disturbance occurrence and $$\Delta_v$$ denotes the distance between the threshold and voltage index after the fault occurrence.

As seen in Table 6, when THD increases from 0.3% to 5.2%, the distance between current and voltage index before the disturbance occurrence ($$\Delta_i$$ and $$\Delta_v$$) decreases but remains positive. However, when THD reaches 6.5%, the values of $$\Delta_i$$ and $$\Delta_v$$ become negative which means the initial values of current and voltage index are greater than the threshold. Therefore, THD = 5.2% can be introduced as a threshold for harmonic contamination situation in the voltage supply.
6.3. Effect of load change

According to the explanations previously given in the load growth scenario, both the current and voltage index values are less than the threshold. Note that $T_{L1}(p.u)$ and $T_{L2}(p.u)$ denote the load values before and after the change, presented in Table 7. As observed, all values of the current index are less than 0.02 and consequently can be considered as normal operating conditions.

![Image of current and voltage signals with time axis](image)

![Image of current and voltage signals with time axis](image)

![Image of current and voltage signals with time axis](image)

![Image of current and voltage signals with time axis](image)

![Image of current and voltage signals with time axis](image)

**Table 5**

Average current index value.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>$R_f(\Omega)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.007 (1 Turn)</td>
<td>0.0333 0.0329 0.0324 0.0245 0.0196 0.0168</td>
</tr>
<tr>
<td>0.01</td>
<td>0.0578 0.0574 0.0572 0.0384 0.0257 0.0191</td>
</tr>
<tr>
<td>0.02</td>
<td>0.0969 0.0963 0.0931 0.0701 0.0583 0.0353</td>
</tr>
<tr>
<td>0.05</td>
<td>0.126   0.1217 0.1203 0.1026 0.0763 0.0687</td>
</tr>
<tr>
<td>0.07</td>
<td>0.137   0.134  0.131  0.1114 0.0981 0.0865</td>
</tr>
<tr>
<td>0.1</td>
<td>0.141   0.1403 0.1391 0.1215 0.0102 0.0971</td>
</tr>
</tbody>
</table>

**Table 6**

Harmonic contamination effect on the proposed index.

<table>
<thead>
<tr>
<th>THD(%)</th>
<th>0.3  1.87  2.29  3.12  4.4  5.2  6.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{c}$</td>
<td>0.019  0.016  0.014  0.008  0.006  0.003  -0.0097</td>
</tr>
<tr>
<td>$\Delta_{v}$</td>
<td>0.021  0.02  0.019  0.01  0.003  0.0006  -0.008</td>
</tr>
</tbody>
</table>

6.4. Effect of Gaussian noise

In the power system, the measured signals are typically noise-impregnated, and as a result, the performance of the proposed index in the presence of Gaussian noises is investigated and the results are presented in Table 8. According to Table 8, as the SNR value decreases from 60db to 20db, the values of $\Delta_{c}$ and $\Delta_{v}$ decrease and finally at SNR = 15db, $\Delta_{c}$ and $\Delta_{v}$ values became negative. Therefore, the suggested index...
falls into maloperation. It should be noted that $P_i$ and $P_n$ denote the power of signal and noise respectively.

6.5. Discussion

As an overall trend, considering the simulation and practical results and performed sensitivity analyzes, it can be argued that:

1. The proposed algorithm can detect low-intensity faults ($\beta = 0.02$) for high values of resistance ($R_f = 100\Omega$).
2. Ability to detect inter-turn faults in the presence of source harmonic pollutions even up to THD = 5.2% in the power systems.
3. A significant performance in the presence of measured noise-impregnated signals even up to 20 db is illustrated in the proposed method due to the utilization of the Kalman filter-based algorithm.
4. The proposed method technically has robustness to non-fault conditions including voltage quality problems (Voltage sag, Voltage swell, Unbalanced Voltage, Voltage Fluctuation due to Capacitor Switching and Parallel Motor Switching) and Heavy Load Changes.
5. Due to straightforward and low computational mathematical basis, the proposed method is computationally efficient.
6. The proposed method has shown promising accuracy and suitable delay in the detection of different conditions.

Although the proposed approach has many positive points. However, considering that the real system may be exposed to other noises such as colored noise in addition to Gaussian noise, the performance of the classic Kalman Filter will be slightly affected. To overcome this problem, it is recommended to use other estimators from the Kalman filter family.

7. Performance comparison of the proposed method with some other State-of-the-Art techniques

For a fair comparison between the proposed method and the other methods, techniques based on MCS and MVS are considered. Here, the results of another techniques based on MCS and MVS in the same practical and simulation data as well as same conditions are investigated.

7.1. Impedance

In [35], for detection of SITF, a technique based on the variation of IM’s equivalent impedance has been carried out. In this method, equivalent impedance of IM in normal condition is defined as reference. Owing to variation of the equivalent impedance in fault condition, the equivalent impedance is normalized respect to reference value and difference between the equivalent impedance and the reference value is defined as fault detection criterion. At the end, by determining a threshold, the criterion value is compared to the threshold value and SITF is detected. The result of normalized impedance changes due to faults for different fault severities are tabulated in Table 9.

7.2. Instantaneous active and reactive power signature

In [18], by processing of active and reactive instantaneous powers can detect the SITF of IM. Generally, this method focuses on the interactions between the existent harmonics in negative components of stator current with the stator voltage in the fault condition. These interactions lead to some harmonics in the spectrum of instantaneous active and reactive powers.

Since a SITF occurs, the instantaneous active and reactive powers formulas of the IM can be as follows. The components $2f, 6f, 10f$ etc are present in the active and reactive power in addition to the DC component.

\[
P(t) = V_s^+I_s^+\cos(\phi) + V_s^-\sum_{k=0}^{\infty} I_k^-\cos(2kot - \phi_k)\]

\[
Q(t) = V_s^+I_s^+\sin(\phi) + V_s^-\sum_{k=0}^{\infty} I_k^-\sin(2kot - \phi_k)\]

The parameters of $V_s^+, I_s^+, I_k^-, f$ and $\phi$ denote the positive component amplitude of stator voltage, positive component amplitude of stator current, negative component amplitude of stator current of order $k$, fundamental frequency and phase of signal.

According to Fig. 21(a) and Fig. 21(b), increase of $2f, 6f$ and $10f$ frequency components in instantaneous active and reactive powers in case of SITF ($\beta = 0.05$) can be seen.

7.3. Instantaneous total harmonic distortions (ITHDs)

In [21], according to (23) and motor specifications, the frequencies of the sidebands harmonics ($I_{in}$) are determined. Afterward, amplitudes of the harmonics are estimated using the Kalman Filter. Eventually, the calculated ITHD using following equation is compared with a predefined threshold. If the value of ITHD is greater than the threshold, SITF is diagnosed.

\[
ITHD_{in} = \sqrt{\sum_{i=1}^{n} \hat{I}_i^2}\]

The result of ITHD values due to faults for different fault severities are tabulated in Table 10.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>0.04</th>
<th>0.06</th>
<th>0.08</th>
<th>0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta Z$</td>
<td>0.005</td>
<td>0.006</td>
<td>0.012</td>
<td>0.019</td>
</tr>
</tbody>
</table>

8

Table 7
Current index value in different load growth rates.

<table>
<thead>
<tr>
<th>$T_1 (p.u)$</th>
<th>$T_{1z} (p.u)$</th>
<th>Current index value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>1.5</td>
<td>0.0166</td>
</tr>
<tr>
<td>0.2</td>
<td>0.6</td>
<td>0.0098</td>
</tr>
<tr>
<td>0.6</td>
<td>0.9</td>
<td>0.0084</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>0.0103</td>
</tr>
<tr>
<td>0.6</td>
<td>1.3</td>
<td>0.01437</td>
</tr>
<tr>
<td>0.3</td>
<td>0.9</td>
<td>0.01401</td>
</tr>
</tbody>
</table>

Table 8
Gaussian noise effect on the proposed index.

<table>
<thead>
<tr>
<th>$\Delta f$</th>
<th>$\Delta f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.018</td>
<td>0.015</td>
</tr>
<tr>
<td>0.014</td>
<td>0.01</td>
</tr>
<tr>
<td>0.005</td>
<td>0.002</td>
</tr>
<tr>
<td>0.009</td>
<td>-0.0097</td>
</tr>
<tr>
<td>0.001</td>
<td>-0.0095</td>
</tr>
</tbody>
</table>

Table 9
Normalized impedance changes $\Delta Z$ for different fault severities ($\beta$).

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>$\Delta Z$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.04</td>
<td>0.005</td>
</tr>
<tr>
<td>0.06</td>
<td>0.006</td>
</tr>
<tr>
<td>0.08</td>
<td>0.012</td>
</tr>
<tr>
<td>0.1</td>
<td>0.019</td>
</tr>
</tbody>
</table>
7.4. Instantaneous frequency (IF)

In [20], the variation of estimated Instantaneous Frequency (IF) has been utilized for detection of SITF in IM. Comprehensively, it can be said that the suggested method uses the signatures in both time and frequency domains.

At the onset, a empirical mode decomposition (EMD) is applied to stator current and intrinsic-mode functions (IMFs) are extracted. Afterward, the first IMF of the EMD is selected and its IF is estimated using adaptive IF estimation. The variation of the estimated IF ($\Delta$IF) is utilized as the criterion for the detection of SITF. Finally, if the IF value decreases more than predefined threshold, the SITF is detected. In Table 11, the results relevant to variation of estimated Instantaneous Frequency (IF) for different fault severities is provided.

7.5. Discussion

In this section, the performance of this proposed method with four similar techniques is investigated from several aspects and the results are tabulated in Table 12. These aspects include delay time, analyzing domain, the required signals, accuracy for 450 simulation cases and 50 practical data case, robustness to voltage quality problems (Voltage sag, Voltage swell, Unbalanced voltage, Voltage fluctuation due to Capacitor Switching and Parallel Motor Switching), robustness to noise.

According to Table 12, although the [35] has a delay of 0.02 s and its analyzing domain is time as well as is robust to voltage imbalances. But, its biggest drawback can be considered low accuracy in detecting various conditions. To overcome this problem, the utilization of [18] for detection of faults is recommended which has a suitable delay of 0.01 s and better accuracy in simulation (82%) and practice (76%), but this method due to the impact of selecting the appropriate window length in FFT-based methods on the accuracy is unable to detect low intensities faults and suffers from lack of robustness to voltage sag, voltage swell and voltage transient fluctuations such as capacitor switching and parallel motor switching.

In [21], although it uses only the current signal as the input of the algorithm and also has a better accuracy of about 90% in simulation and 83% in practice. However it has no robustness to none of the voltage quality problems scenarios and also high sensitivity to gaussian noise. [20] has a much higher accuracy and its input signal is only current and is robusted to gaussian, but it has a maloperation against the voltage sag, voltage swell and voltage transient oscillations.

The proposed method with a low computational approach has been able to solve the problems of other methods so that by changing in how the data window is updated from one cycle to half cycle, the time delay can be decreased to 0.01 s and show a very significant accuracy of about 94% in simulation and 91% in practice. It also has robustness to voltage quality problems, gaussian noise and harmonic contamination in the supply voltage.

8. Conclusion

Due to the importance of IMs in industries, the monitoring of the healthiness of IMs is very essential. This paper concentrated on the SITF detection in IMs. To this end, a Kalman filter-based approach was proposed to obtain MCS and MVS of the current and voltage signals respectively. Afterward, the standard deviation of the residual signal (i.e. the difference between measured and estimated signals) was introduced as a fault detection index. To enhance the robustness, the proposed method voltage quality problems, voltage signal was used as an auxiliary signal. To evaluate this method, plenty of simulation and experimental tests were performed and according to the results, the performance of the proposed method was compared with some MCS-based and MVS-based methods. It was observed that the proposed index has a robust performance for different fault resistance considering different fault intensities. Moreover, the proposed index can deal with the voltage quality problems such as voltage sag, voltage swell, unbalanced supply voltage, and harmonic contamination in the supply voltage. Furthermore, the proposed index has immunity against a wide range of load changes. Eventually, the proposed method can operate in a high level of noisy conditions. The main superiorities of the proposed method compared to the state-of-the-art algorithms include (a) the most accurate in diagnosing conditions (b) capability of proposed method in detection of faults in 0.02 s and even reduction to 0.01 s with a change in how the data window is updated from one cycle to half cycle (c) robustness to voltage quality problems. Given that the practical noises

| Table 10 | ITHD values for different fault severities ($\beta$).
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.03</td>
</tr>
<tr>
<td>ITHD</td>
<td>0.29</td>
</tr>
</tbody>
</table>

$\Delta$IF value for different fault severities ($\beta$).

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>0.02</th>
<th>0.05</th>
<th>0.07</th>
<th>0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta$IF</td>
<td>-1.43</td>
<td>-2.17</td>
<td>-2.57</td>
<td>-3.37</td>
</tr>
</tbody>
</table>

| Table 12 | Comparison of the proposed method with similar methods based on MCS and MVS.
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Comparative aspects</td>
<td>[35]</td>
</tr>
<tr>
<td>Delay time (s)</td>
<td>0.02</td>
</tr>
<tr>
<td>Analyzing domain</td>
<td>t-f</td>
</tr>
<tr>
<td>The required signals</td>
<td>I-V</td>
</tr>
<tr>
<td>Accuracy for simulation (%)</td>
<td>78</td>
</tr>
<tr>
<td>Accuracy for practical data (%)</td>
<td>71</td>
</tr>
<tr>
<td>Robustness to gaussian noise</td>
<td>No</td>
</tr>
<tr>
<td>Robustness to voltage sag</td>
<td>No</td>
</tr>
<tr>
<td>Robustness to voltage swell</td>
<td>No</td>
</tr>
<tr>
<td>Robustness to unbalanced voltage</td>
<td>Yes</td>
</tr>
<tr>
<td>Robustness to capacitor switching</td>
<td>No</td>
</tr>
<tr>
<td>Robustness to parallel motor switching</td>
<td>No</td>
</tr>
</tbody>
</table>
are modeled as Gaussian noise usually. In this way, the KF is used as a suitable tool for analyzing harmonic components in the presence of noise. In practice, there may be another noises such as colored noise in which case, the use of Extended KF, Unscented KF and even Particle Filter for non-linear systems can be suggested.

CRediT authorship contribution statement

Ali Namdar: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Software, Writing – original draft, Writing – review & editing. Haidar Samet: Investigation, Methodology, Data curation, Funding acquisition, Project administration, Resources, Supervision. Mehdi Allahbakhshi: Investigation, Project administration, Supervision, Writing – review & editing. Teymoor Ghanbari: Data curation, Resources, Writing, Review – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References