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Eccentricity Fault in Induction Motors Using Statistical Process Control Method

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Abstract

Induction motors are the most commonly used electric motors in the industry. The main reasons for choosing induction motors are their robust structure and low maintenance requirements. However, the harsh working conditions of the industry cause motor faults. Predicting motor faults in advance or determining the cause of fault is very important for businesses. In this study, an attempt was made to detect the eccentricity fault of the induction motor with a cheap and easy method. The eccentricity fault, which is a mechanical fault and is frequently encountered, was tried to be determined by monitoring the motor current signals. The motor current signals were analyzed with the statistical process control method from statistical methods. For the first time, with this study, the eccentricity fault occurring in an induction motor operating under different speed conditions was successfully detected with the statistical process control method.

Keywords: "Eccentricity fault, statistical process control, induction motors."

1. Introduction

Electric motors are one of the most important drive elements of the industry[1]. It is used very intensively in household applications. In addition to its intensive use, electric motors have an important place in electrical energy consumption in the world with a rate of 45%. Induction Motor (IM) stands out as the most preferred motor of the industry and therefore the most energy consuming motor. IMs are preferred due to their robust and simple structures, not requiring much maintenance and being able to travel on their own [2], [3].

IMs, which are used extensively in the industry, operate under many challenging effects. In addition to effects such as unbalanced load formation, ripples in supply voltage, environmental effects such as dusty, humid and hot environment cause both electrical and mechanical faults in IM. Electrical faults seen in these motors are stator winding fault, rotor rod and ring broken faults, mechanical faults are bearing faults and eccentricity faults(EF) [4].

After the IM malfunctions, it can continue to operate in the system. However, the malfunctioning IM operates with low efficiency. In addition to causing an increase in costs, the malfunctioning IM may also cause the business to stop if the malfunction progresses. Unplanned stops will cause time, economic and quality losses [5], [6].

Condition monitoring techniques are used to identify and prevent faults occurring in engines before they grow. The operation of the engine can be monitored continuously or intermittently and with condition monitoring techniques, maintenance time can be determined in advance or faults can be prevented before they grow. During condition monitoring in IM, vibration, acoustic, chemical, magnetic, thermal and electrical data are collected and processed. Especially current signal data collection from electrical data is highly preferred in condition monitoring due to its ease of collection and being the most economical method [7], [8].

The signals obtained through condition monitoring are analysed using time, frequency and time-frequency methods, thus extracting the characteristics of the signals and performing fault detection. Time dimensional analyses allow direct fault detection from raw data, do not require additional mathematical operations and enable the process to be completed quickly. For this reason, time dimensional analysis methods have been widely preferred in the literature and motor faults have been detected by using statistical properties of signals such as mean, peak value and kurtosis [9], [10].

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Statistical Process Control (SPC), a statistical analysis method in time dimension, is widely used in many engineering fields. SPC is a statistical technique developed to improve quality, detect defects and optimise process efficiency in production systems. One of the most frequently used analysis tools within the scope of this method is control charts. In control charts, the lower and upper limits drawn parallel to the X-axis determine the quality working range and the process is monitored with these charts. Thus, negative situations in the process can be detected and intervened early [11], [12].

In this study, condition monitoring is performed based on IM current data and it is aimed to detect the fault onset moment and to monitor the fault development process with the SPC method in time dimension. This method makes it possible to detect faults in advance without experiencing involuntary stops in IMs used in the industry, thus enabling faults to be diagnosed in a short time. In this way, productivity losses due to failures will be reduced and maintenance costs will be reduced. In this study, the static EF of the IM is analysed by SPC method. The EF is analysed under different load constant speed and constant load different speed conditions, in two different operating states and two different power ratings. The EF was artificially induced in the motor and the IM current signal data obtained from the experimental setup were collected for the intact and faulty conditions. With the intact condition data, the quality operating ranges of the SPC were calculated and graphs were created. The data obtained from the IM with EF were processed on the quality operating range and the time of occurrence and presence of the fault were determined.

2. Induction Motors

Among the electric motors, IMs are the most preferred by the industry with a rate of 90%. The advantages of IM such as cheap price, simple structure, low maintenance requirement and self-propelled are among the reasons why IM is preferred. IM consists of stator, rotor, body, bearings and covers. Although the stator is mechanically fixed, it creates a rotating magnetic field with the current applied to its windings. The rotor rotates mechanically with the help of short-circuit currents flowing under the influence of the voltage induced in the windings or rotor rods. The fact that it has a structurally simple structure also emphasises the robustness of IMs. Although they have a robust structure, these motors operating under harsh operating conditions may fail involuntarily [2], [3], [13].

3. Faults in Electrical Machines

IMs operating under severe operating conditions are exposed to mechanical and electrical faults due to their structure. IM faults, which are basically categorised under two headings, are shown in the fault diagram given in Fig. 1.

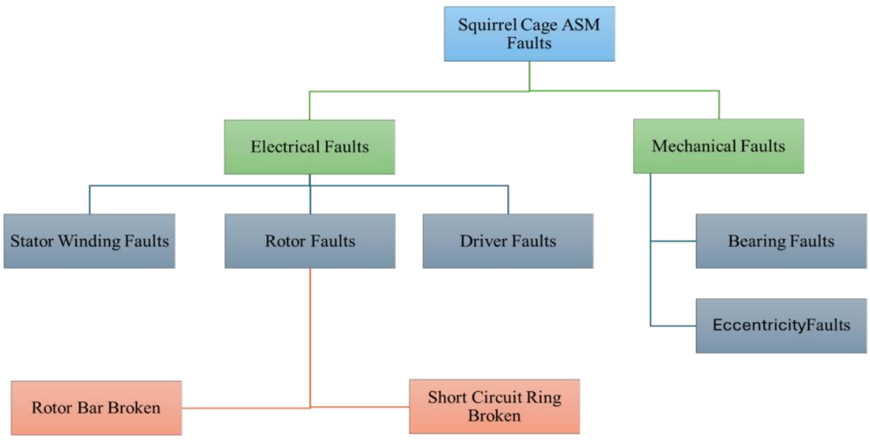

Fig. 1. IM faults.

Electrical faults seen in IMs are categorised into 3 groups and constitute 48% of the total faults [14]. The main effects causing mechanical faults are non-axialisation of the load and the motor, unbalanced and overload conditions, dust and lubrication faults [15]. While bearing faults develop over time, EF can occur even at the time of initial assembly. In this study, the detection of EF is studied.

3.1. Eccentricity Faults

In IM, the relationship between the stator and the rotor is provided through the air gap and the power transmission is carried out as a magnetic field through the gap. Eccentricity is the condition of unequal distribution in the air gap [4], [15]. EFs can occur later or at the time of initial production. Manufacturers have determined the margin of error as 5%-10% and produce with this precision. Bending of the motor shaft, slipping of the connection couplings between the motor and the load from the axis and wear of the bearings cause EFs [17], [18].

In case of EF, there are disturbances in the flux generated in the air gap. Increase in flux amplitude, instability in motor input currents, increase in torque ripple and decrease in average torque, temperature increase are among the consequences of EF. The growth of EF results in the rotor rubbing against the stator [19], [20].

EFs are divided into three as static EF, dynamic EF and mixed EF. The constant slip between the stator axis and the rotor axis is defined as static EF. The unbalanced forces caused by this fault create a constant thrust in one direction. Static EF occurs when the stator or rotor cores are not perfectly round but oval and the centres of the stator and rotor axes are not exactly coincident. In case of dynamic EF, the slip between the stator axis and rotor axis is mobile. In mixed EF, both (static + dynamic) EF are observed together [21], [22].

EFs can be detected by analysing current and voltage signals. When the spectra of current and voltage signals are examined, it is seen as sideband. The location of the EF in the sideband is calculated by Equation 1 [19], [22].

$$f_{MF} = \left[1 \pm \left(\frac{2k-1}{p}\right)\right] f_e \tag{1}$$

Here f_{MF} is the EF frequency, $k = 0,1, \ldots, n$ is a fixed value, p is the motor pole pair, f_e is the motor electrical supply frequency.

4. Fault Detection Methods in IM

IM faults cause great losses due to the places where they are used. In the industry, condition monitoring methods are developed to prevent these faults and to identify the fault in a short time. With condition monitoring methods, it is possible to detect the fault in advance and shorten the maintenance time. Many signals and data such as vibration, electromagnetic field, induced voltage, air gap electromagnetic moment, thermal and current signal monitoring are analysed to detect IM faults [14], [23].

Among these methods, monitoring of motor currents is one of the most preferred methods due to the need for cheap materials, easy acquisition and ease of installation. There are three main causes of harmonics in current signals. These are supply source and production errors and faults in the motor. According to the type of faults occurring in the motor, stator current signals create harmonics. Especially mechanical failures such as bearing and EF etc. disrupt the flux distribution in the air gap. Distortion of the flux distribution causes the motor inductance value to change and this causes harmonics in motor currents [14], [24].

4.1. Signal Processing Methods Used in Fault Detection

In order to characterise a system or material, it is necessary to extract its properties. In electric motors, fault detection is performed by extracting the characteristics of the data obtained. The most preferred methods of feature extraction for fault detection in electric motors are frequency dimensional analysis, time-frequency dimensional analysis and time dimensional analysis [25], [26]. The simple acquisition of time domain signals makes the method easy and inexpensive. According to the characteristics of the signals analysed in time dimension, their characteristics are extracted by using statistical analysis methods. Many statistical parameter values such as kurtosis, variance, skewness, mean value and standard deviation are obtained and used in fault detection of electric motors [27].

Especially in the industry, SPC, in which statistical parameters are analysed, is preferred in order to increase the quality and to monitor the process in the wear of machine parts. In this study, SPC is used to monitor the engine operation process and to detect the malfunction

4.2. Statistical Process Control

SPC is widely used in manufacturing processes to improve quality, detect faults and make the process run even more efficiently. The system is realised by analysing data such as vibration, number of defects, weight, power and current collected during the working process [11], [12]. While performing process control with this method, there is no need for continuous monitoring. Data sets are created with periodic or random measurements and the process is evaluated. The samples created by measurements reveal the changes in the process and consequently the defects in the product. SPC analyses the relationship between the product and the process [28], [29].

Some techniques such as tally, pareto analysis and control charts are used to identify and analyse the problems that may occur in the process and to examine the data needed [29]. Control charts analyse a process containing control limits by processing the data obtained. While changes due to natural causes remain within the limits, changes in the process due to special causes result in exceeding the limits. Problems are solved by determining the time and the special causes in the process [30]. The sample control graph is shown in Fig. 2.

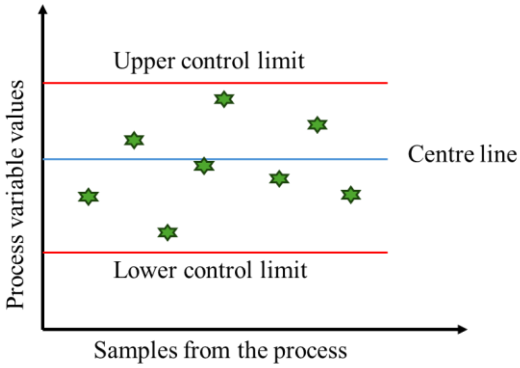

Fig. 2. Control chart.

SPC graphs provide visual information about the system. Upper and lower control limits are created with the data received from the robust system and then the collected data is processed. When an out of limits or unusual operation is detected, the system is stopped or the error is eliminated during operation. Visual examination of the process with control charts enables easy detection of errors. The system is continuously monitored by processing the data received from the system [30], [31].

While creating the control charts, the mean $\bar{X}$ and the difference in the process (R) values and the standard deviation values (S), which examine the mean values ($\bar{X}$) and subgroup changes, are evaluated. $\bar{X} - S$ control charts are preferred in data sets with a larger sample volume. Both graphs are analysed together when evaluating the operation of the process. Long-term changes in the process are seen in $\bar{X}$ control graphs and short-term changes in S control graphs [11]. The analytical average of the data taken from the system, $\bar{X}$ and the central line $\bar{\bar{X}}$ are calculated as in Equation 2 and Equation 3.

$$\bar{X} = \frac{\sqrt{\sum_{i=0}^{n}(x_i)}}{n} \tag{2}$$

$$\bar{\bar{X}} = \frac{\sqrt{\sum_{i=0}^{m}(\bar{X}_i)}}{m} \tag{3}$$

Here, the sample taken from the system is expressed as x_i , the number of groups of the sample is expressed as m and the number of samples in a group is expressed as n.

S the centre line and the lower and upper limits of the S control charts;

$$S = \frac{\sqrt{\sum_{k=0}^{n}(x_i - \bar{x})^2}}{n-1} \tag{4}$$

$$\bar{S} = \frac{1}{m}\sum_{i=1}^{m}(S_i) \tag{5}$$

$$UCL_s = B_4\bar{S} \tag{6}$$

$$CL_s = \bar{S} \tag{7}$$

$$LCL_s = B_3\bar{S} \tag{8}$$

The standard deviation value calculated for each of the sample groups is expressed as S and the mean value of all of them is expressed as $\bar{S}$. B_3 and B_4 values can be taken from the control charts table for different subgroup numbers [11]. The $\bar{S}$ value is used when calculating the central line and limits of the average control graphs created to examine the long-term errors that will occur in the system.

$$UCL_X = \bar{\bar{X}} + A_3\bar{S} \tag{9}$$

$$CL_X = \bar{\bar{X}} \tag{10}$$

$$LCL_X = \bar{\bar{X}} - A_3\bar{S} \tag{11}$$

Here A_3 represents a factor value used to organise the variable quantity control graphs.

5. Experimental Study

In order to perform accurate fault detection in electric motors, current signals must be reliable. In this study, the experimental setup to generate the data set is designed for precise data collection. The schematic and experimental setup designed for fault detection is shown in Fig. 3.

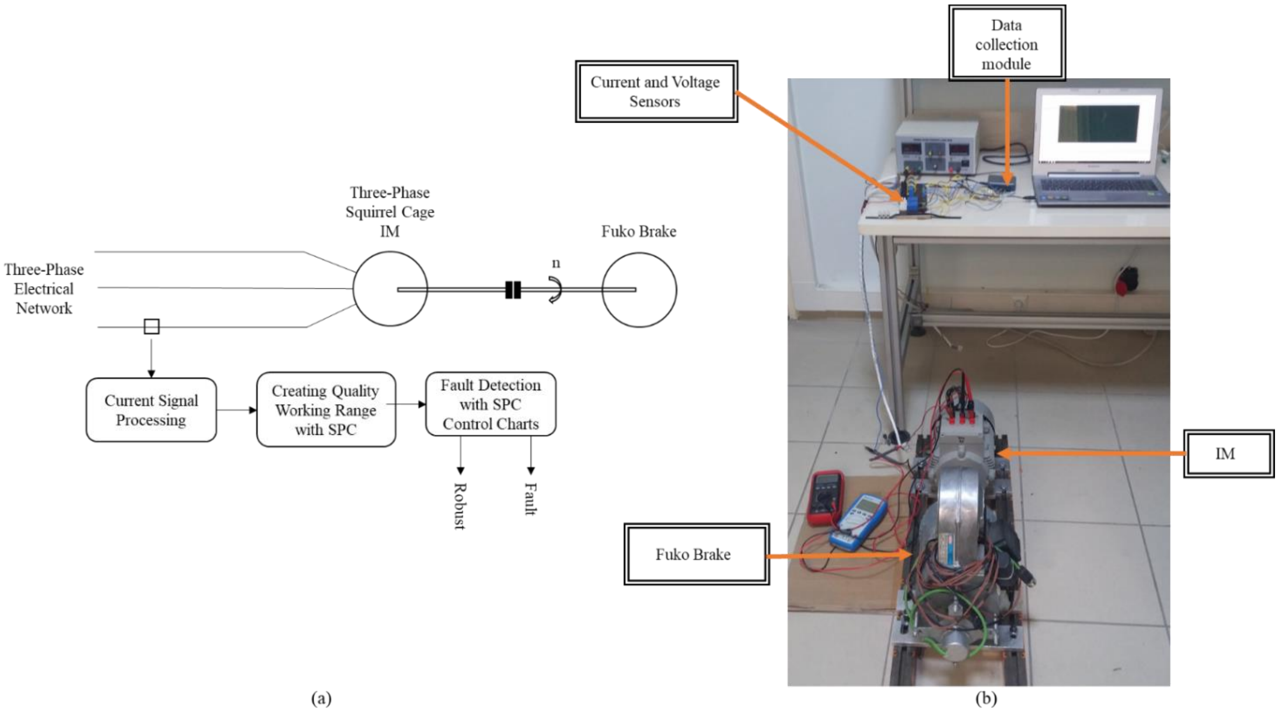

Fig. 3. (a) Experimental schema; (b) Experimental set-up.

For fault detection, intact and faulted state data were obtained from two identical IMs. As shown in Fig. 3, the experimental set consists of IM, Data acquisition module, Current and Voltage sensors, Fuko Brake and Motor driver. The parameter values of the IM used are given in Table 1.

Table 1. IM parameters.

Parameter	Value	Unit
Power	750	W
Frequency	50	Hz
Voltage	220/400 (Δ/Y)	V
Current	2.90/1.67 (Δ/Y)	A
Speed	2805	d/d
$\cos\varphi$	0.84	
Number of poles	2	

In this study, the operating conditions of the IM at different speed values are analysed and fault detection is performed. EF can be caused by the connection between the motor and the load. Considering this situation, although the motor was operated without load, its connection with the fuko brake was realised. The fact that the motor and the load are on the same axis ensures that the targeted EF signal is obtained precisely. A laser axing device was used to axialise the motor and the load. The laser axis device is shown in Fig. 4.

Fig. 4. Laser axisising device.

As shown in the figure, the laser axis device is connected between the motor and the load with the connection elements. After the connection is completed, the measurement is performed and according to the result, the motor or load side is adjusted in x or y axes. After the load and the motor shafts are axialised the same, the fixing process is performed.

The current signal data of the IM were recorded to the computer with the data acquisition module. The data acquisition module used has 16*bit resolution and collects data simultaneously with a sampling rate of 50ks/sec and records it in a virtual environment via software. Data collection operations were performed for 5000 Hz sampling robust and EK failures. The motor was operated at 3 different speeds of 1000 rpm, 2000 rpm and 2991 rpm and data sets were created.

In order to create the situation with EF, the bearing of the IM was replaced and a new bearing was installed. Instead of the removed bearing, a bearing with the same inner diameter and smaller outer diameter was designed. A separate material called baga was mounted on the outside of the new bearing and the shaft was shifted to one side in a fixed direction from the axis. The bearings used to create this assembly EF are given in Fig. 5.

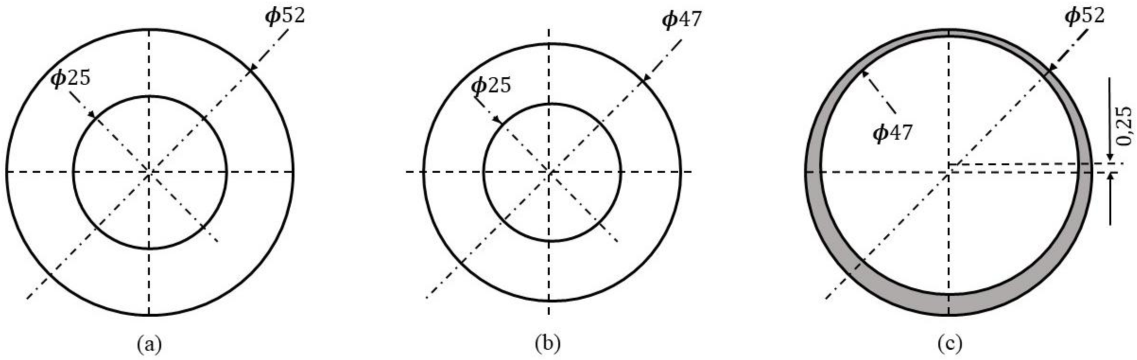

Fig. 5. Bearing shapes used in the creation of the EF (a) IM original bearing; (b) New bearing; (c) Baga.

The following steps were followed in the experimental study and fault diagnosis applications:

Step 1: Collecting the signal data of the motor currents from the intact and EF motors,

Step 2: Robust and EF data sets were prepared and statistically analysed,

Step 3. SPC graphs are generated and diagnosed.

While processing the collected current signal data, the data taken in periods were divided into sample groups. The maximum values of the sinusoidal signals were determined and SPC graphs were created.

5.1. Results and Discussion

In this study, the EF of the IM is tried to be detected by the proposed SPC method. In the proposed fault detection method, it is aimed to determine the EF by comparing the intact and faulty current signal data. Quality control cards were created with the current signal data set obtained from the intact IM. The fault is detected by adding the current signal data from the faulty IM to the process of the control cards. IM current signal is shown in Fig. 6.

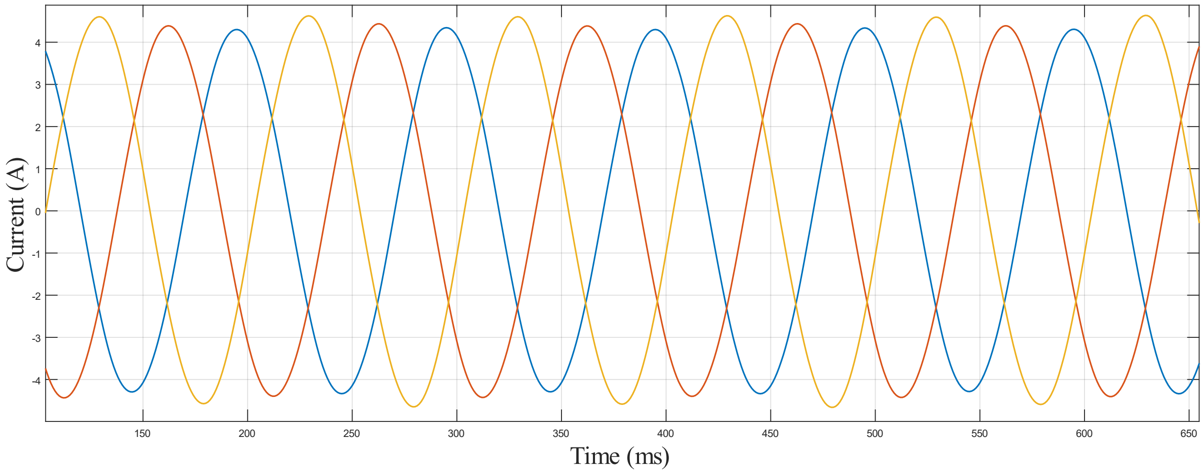

Fig. 6. Three-phase IM current signal.

Data sets were created with 50 peak values taken at 10 different times for intact and faulty conditions. The 750 W IM controlled by the driver was operated in 3 different speed states. The speed control of the motor is provided by a voltage frequency (V/f) controlled driver. In order to have 500 peak values in the data sets in healthy and faulty conditions, the IM was operated for 15.5 s at 1000 rpm, 7.75 s at 2000 rpm and 5 s at nominal speed and current signal data were recorded.

The current signal data of the IM in healthy and faulty conditions were collected at 1000 rpm and analysed with SPC. The generated and control graphs are shown in Fig. 7.

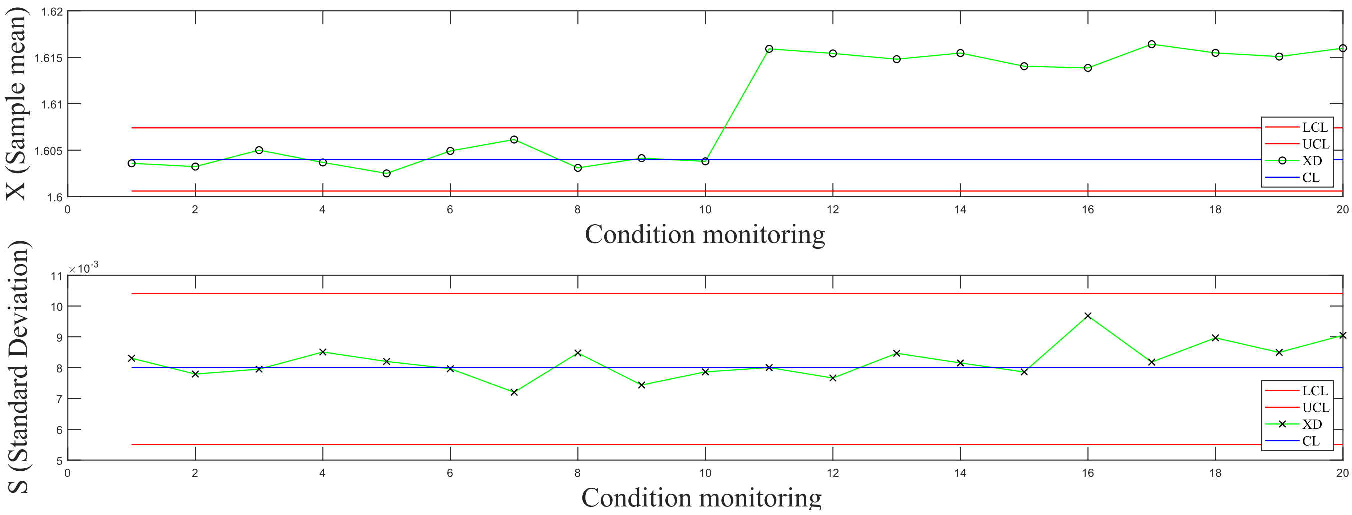

Fig. 7. 1000 rpm speed $\overline{X}$-S control charts.

Table 2. Limit values of $\overline{X}$-S control graphs at 1000 rpm speed.

	LCL	CL	UCL
$\overline{X}$	1,6006	1,6040	1,6074
S	0,0055	0,0080	0,0104

When the control graphs in Fig. 7 are examined, it is seen that the process is normal until the 10th state monitoring moment, that is, the motor is intact. However, when the current signal data of the motor in the faulty state is included in the process from the 11th state monitoring moment, especially in the $\bar{X}$ control chart , the change is noticeable. It is clearly seen that the limits shown in Table 2 are exceeded. Since EF is continuous, S, which determines short-term faults, could not be clearly detected in the control charts. However, it is determined that there is deterioration in the process from the 16th state monitoring moment.

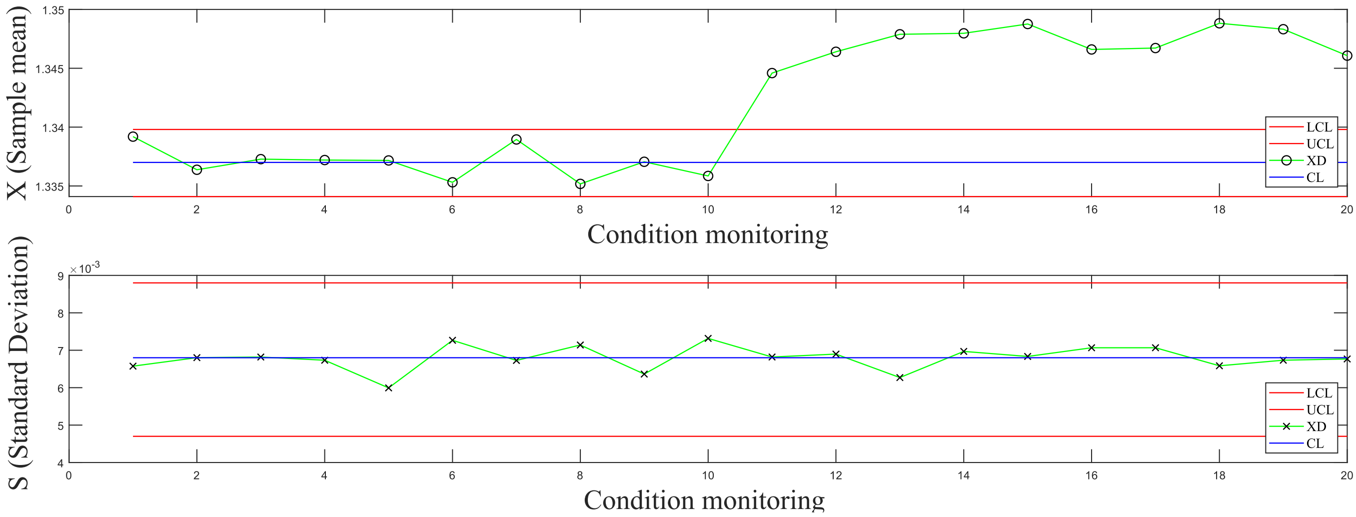

Fig. 8. 2000 rpm speed - control graphs.

Table 3. 2000 Limit values of $\bar{X}$-S control graphs at 1000 rpm speed.

	LCL	CL	UCL
$\bar{X}$	1,3341	1,3370	1,3398
S	0,0047	0,0068	0,0088

As seen in Fig. 8, it is seen in the $\bar{X}$ control chart that EF occurs in the process from the 11th state monitoring moment. However, in the S control chart, it is seen that the process proceeds normally. In order to say that there is no fault in the control graphs, both control graphs should exhibit normal behaviour.Especially after the 11th state monitoring moment of the $\bar{X}$ control graph, it is seen that the limits given in Table 3 are exceeded.

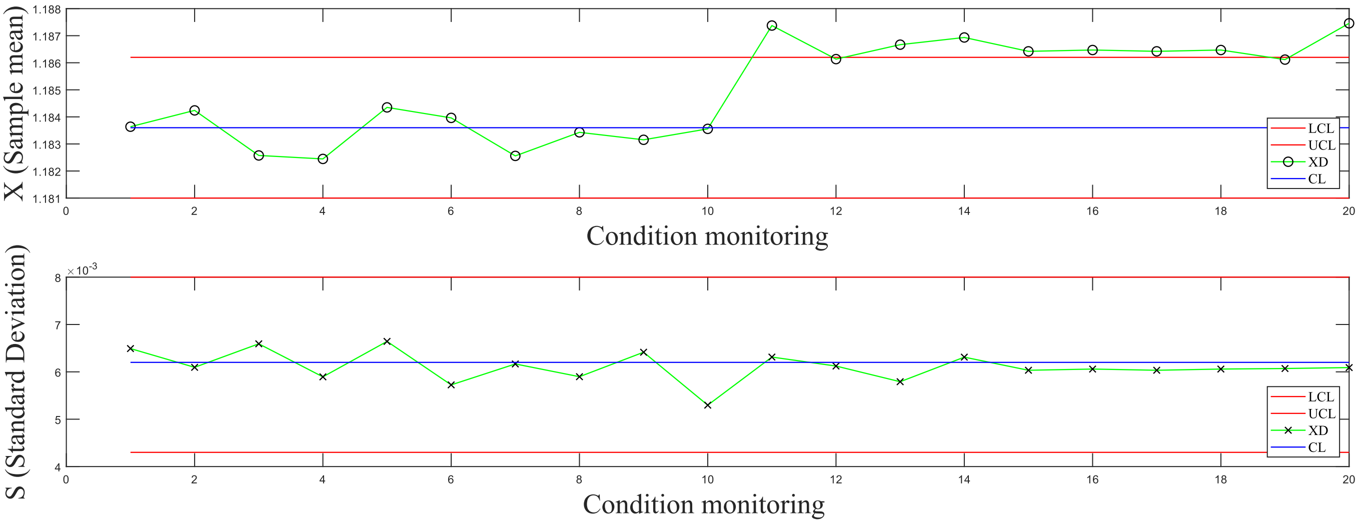

Fig. 9. 2991 rpm speed - control graphs.

Table 4. Limit values of $\bar{X}$-S control graphs at 2991 rpm speed.

	LCL	CL	UCL
$\bar{X}$	1,1810	1,1836	1,1862
S	0,0043	0,0062	0,0080

When Fig. 9 is analysed, it is seen that the UCL value given in Table 4 is exceeded in the $\bar{X}$ control chart starting from the 11th monitoring moment. In the continuation of the process, although it is entered into the range of control limits at the 12th and

19th state monitoring moments, it does not mean that the out-of-control situation in the process has improved. In the *S* control chart, it is determined that the process continues below the CL starting from the 15th state monitoring moment and 6 state monitoring moments occur here. This situation shows that there is an out of control situation and the process continues out of the ordinary. EF was also detected at 2991 rpm speed.

6. Conclusion

In this study, the EF of the IM was determined by SPC over the current signal data. Intact and faulty data sets were created with current signals taken at random times from the IM. With the intact data sets, process control was performed over the control graphics. In the continuation of the process, the current signal data received with EF were processed into control graphs. EF was clearly detected on the control graphs. With the study carried out, the detection of the EF of the IM has been used for the first time in the literature. With the results obtained, fault detection in IM has been obtained easily and inexpensively. The studies and control graphs reveal the success of the fault detection method.

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