Chapter 4

Inter-turn Fault Detection of Three Phase Induction Motor

4.1 Introduction

The internal faults of Induction Motor (IM) accounts for more than 70% in proportion of total IM failures. Internal faults include stator as well as rotor faults in an IM. Rotor faults are related to broken rotor bar/end-ring. They are caused by a combination of various stresses that act on the rotor and these stresses can be identified as environmental, electromagnetic, thermal, dynamic, environmental and mechanical. Therefore these leads to low-frequency torque harmonics, which increases noise and vibration [186, 187]. Occurrence of inter turn fault and failure of the cooling system arises due to increase in stator temperature. Two thermal profile indicators with thermal analysis of the infrared thermography (IRT) images is accomplished in this work [188].

Inter turn fault cause a large circulating fault current in the shorted turns, leading to localized thermal overloading. This one can cause open-circuit failures (melting of conductors), and electrical fire. Voltage unbalance produces negative sequence current, which decreases the motor efficiency and accelerates motor degradation due to increased thermal/mechanical stresses [189, 190]. In fact, a more precise model of the machine is necessary for an accurate analysis of the machine behavior in both healthy and faulty cases [191]. A detailed analysis of short circuit faults requires a precise model. The models of the induction machine, such as the multi winding model, multi-turns and the model of Park [192] are not practical to make changes in the electrical stator and rotor. They represent the electrical behavior of the equivalent induction machine. They do not take into account the electric or magnetic phenomena such as induced currents, magnetic saturation and the effect of complex geometry.

Inter turn fault cause a large circulating fault current in the shorted turn, leading to localized thermal overloading. This one can cause open-circuit failures (melting of conductors), short circuit faults (insulation damage) in the electrical fire [193]. In this chapter the three phase induction motor analysis is done by Ansys-Maxwell software in healthy as well as in faulty condition. An experimental set up has been made for the analysis of current signature of the induction motor in 16 channel CRO, current signature analysis has been done by the FFT and THD evaluation is also accomplished. Finally the fault classification task has been performed by ANN and SVM.

4.2. Design of Three Phase Induction Motor Using Ansys Software

Finite Element Analysis (FEM) is a computer based numerical technique for calculating the parameters of electromagnetic devices. It can be used to calculate the flux density, flux linkages, inductance, torque; induced emf etc., in the FEM, the large electromagnetic device is broken down into many small elements. The behavior of an individual element can be described with a relatively simple set of equations [194]. The computer can solve this large set of simultaneous equations. From the solution, the computer extracts the behavior of the individual elements.

The FEM provides detailed information about the machine nonlinear effects (based on its geometry and material properties). This modeling approach is capable of obtaining an accurate and complete description of an electrical machine [195, 196]. The magnetic circuit is modeled by a mesh of small elements. The field values are then assumed to be a simple function of position within these elements, enabling interpolation of results. The time required to calculate the field distribution may be very long, depending on the number of elements considered [197]. A compromise must be reached between using finer meshes to achieve higher accuracy and the processing resources needed to achieve reasonable simulation times. The FEM is very flexible, especially for new designs incorporating new shapes. However long time simulation requirements reduce its attractiveness for a case when a control algorithm needs to be incorporated [198].

A model of the considered IM (1 hp,3-phase, 440 volt,1400 rpm,36 stator slots,28 rotor slots) has been constructed using ANSYS software in 3D as shown in Figure 4.1.

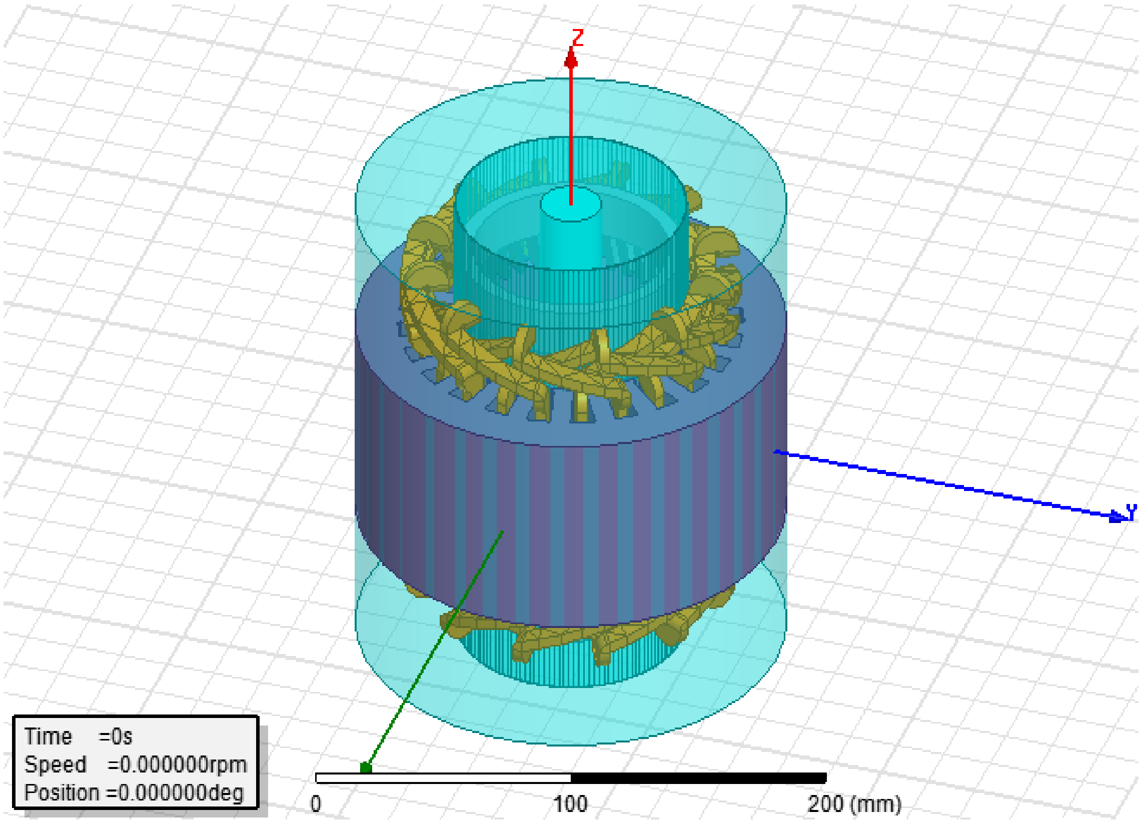

Figure 4.1: ANSYS 3-D model of the considered induction motor.

4.2.1 Performance Analysis of Three Phase Induction Motor in Healthy Condition

The motor performace are carried out by simulation results by Ansys software in healthy condtions. The various performance of induction motor are depicted in following figures.

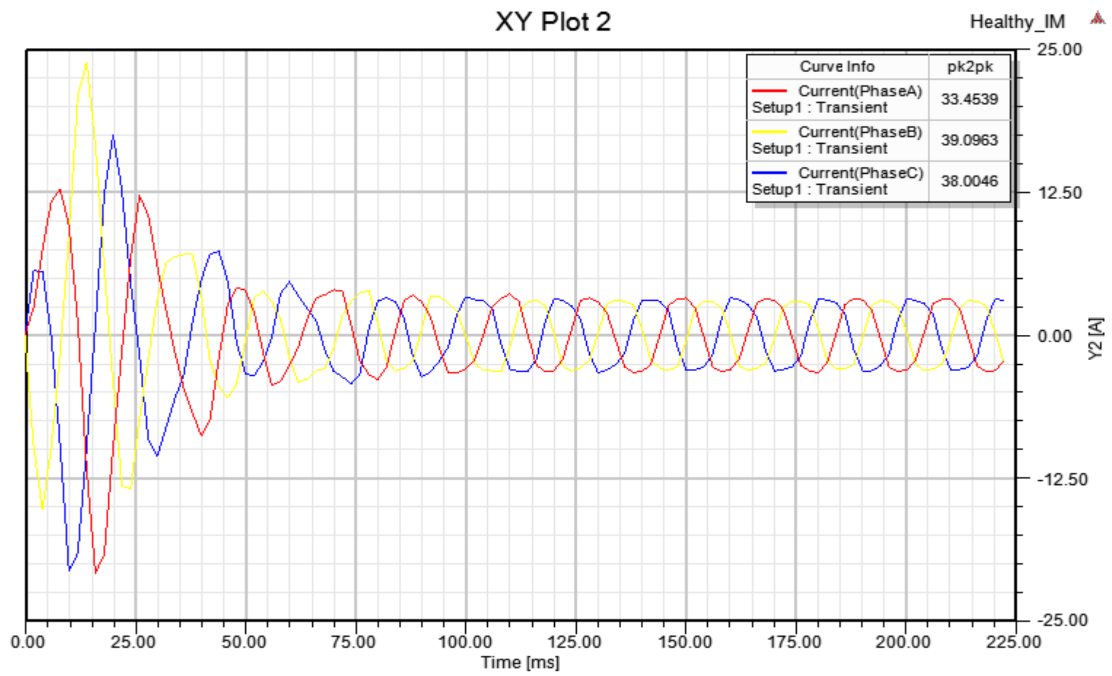

Figure 4.2: Stator winding currents in induction motor.

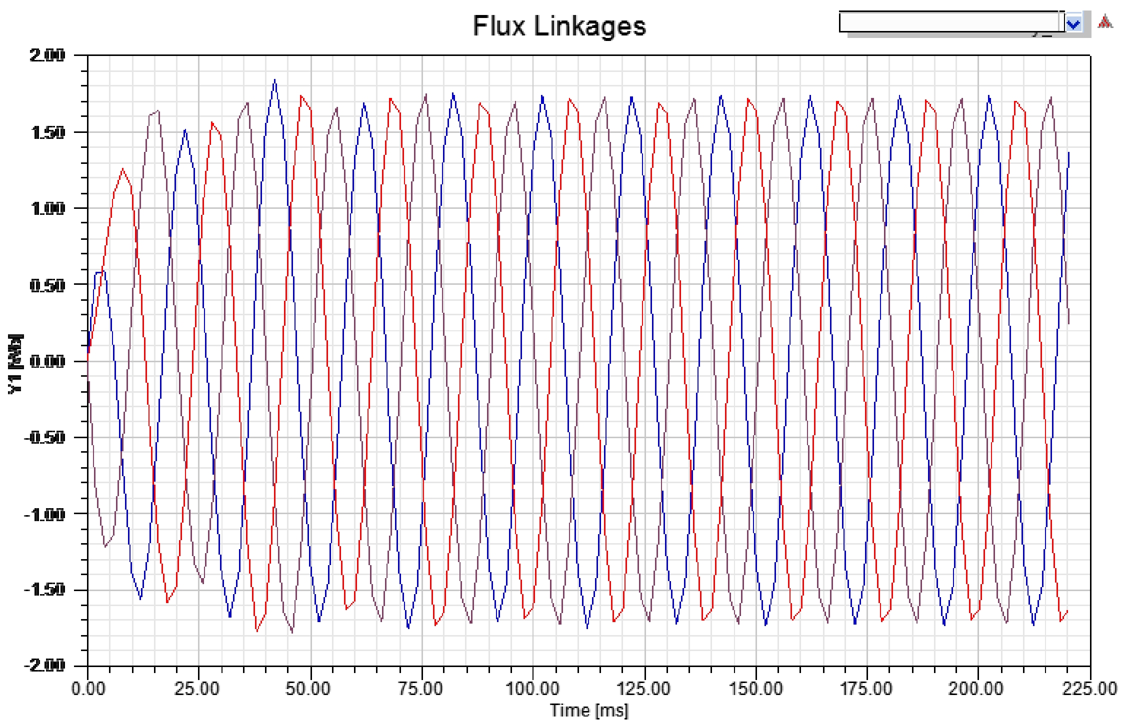

Figure 4.3: Flux linkages in induction motor.

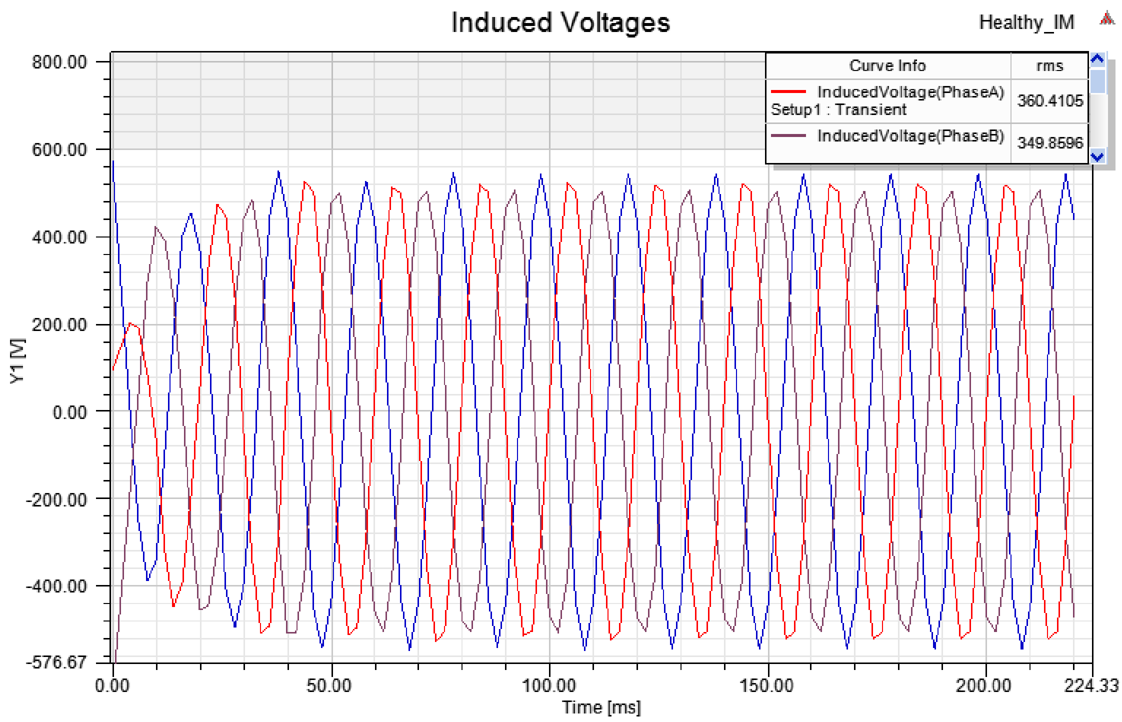

Figure 4.4: Profile of induced voltages in various phases.

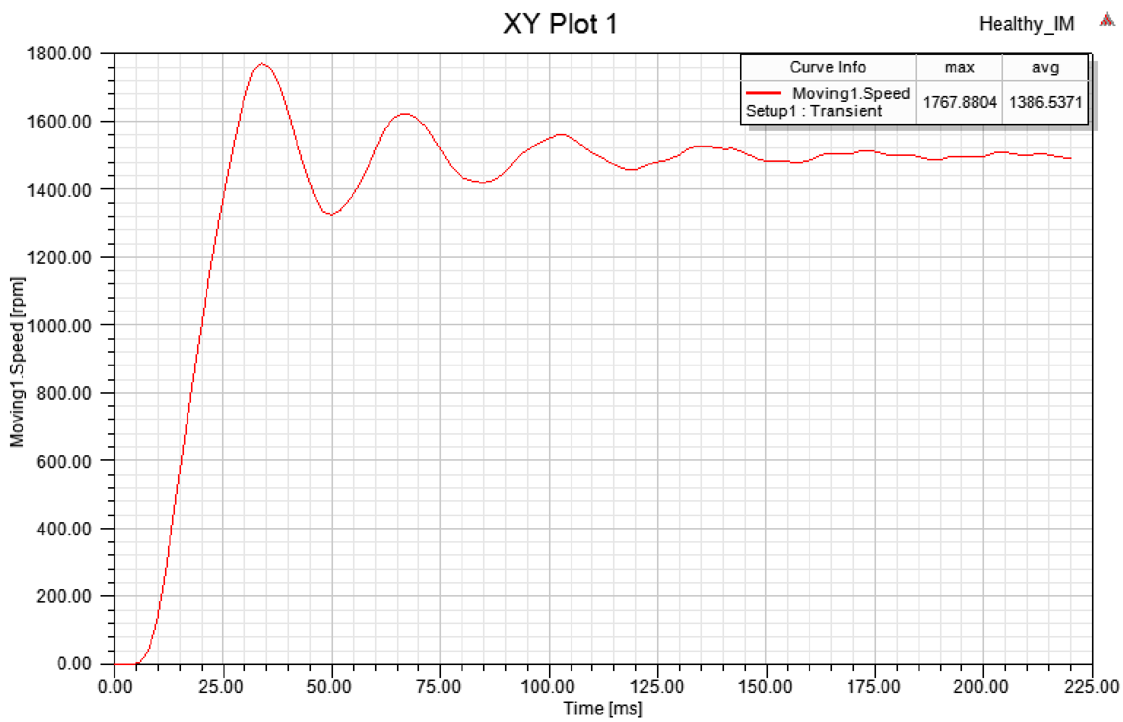

Figure 4.5: Speed profile of induction motor.

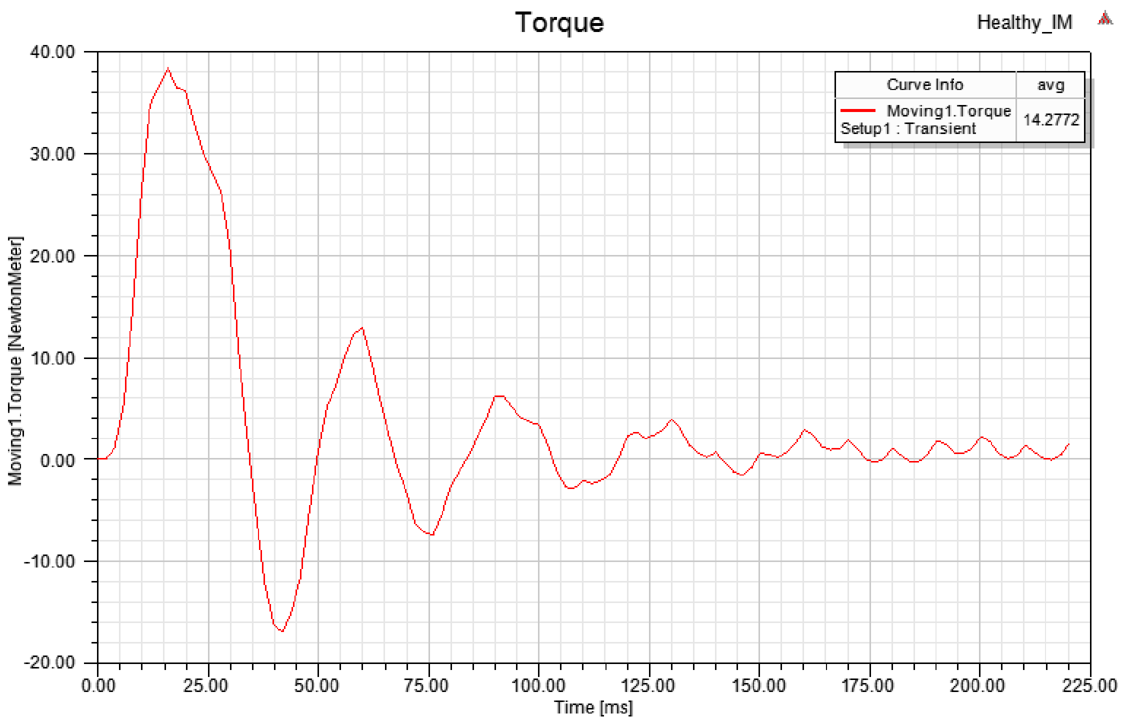

Figure 4.6: Torque profile of induction motor.

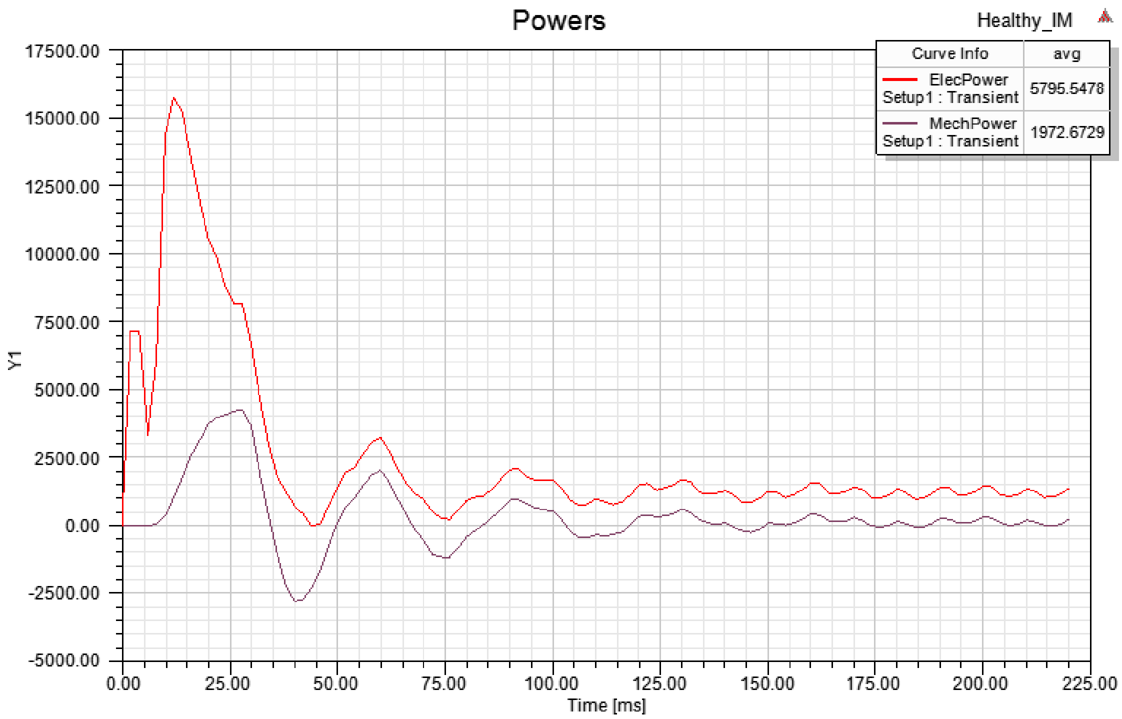

Figure 4.7: Electrical and Mechanical power developed in induction motor.

4.2.2 Performance Analysis of Three Phase Induction Motor in Faulty Condition

The motor performace are carried out by simulation results by Ansys software in faulty condtions(5%, 10%, 15% and 20% of total turns of the phase A). The various performance of induction motor under 5% of total turns shorted in phase A are depicted in following figures.

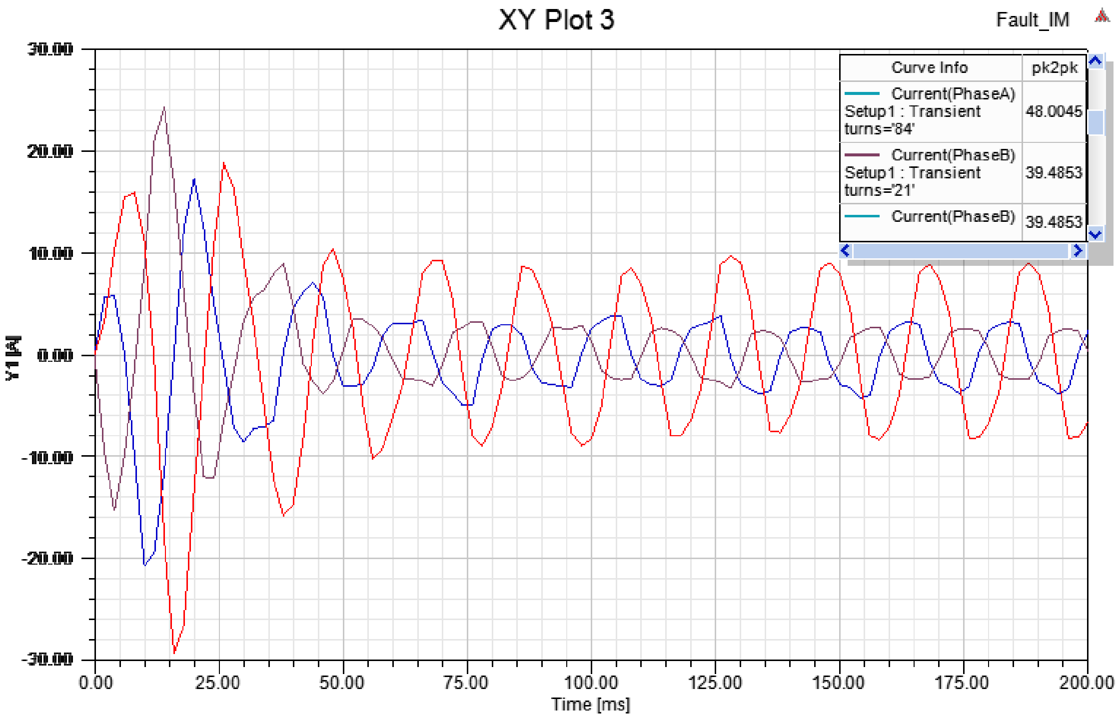

Figure 4.8: Stator winding currents in faulty (5% turn short) condition.

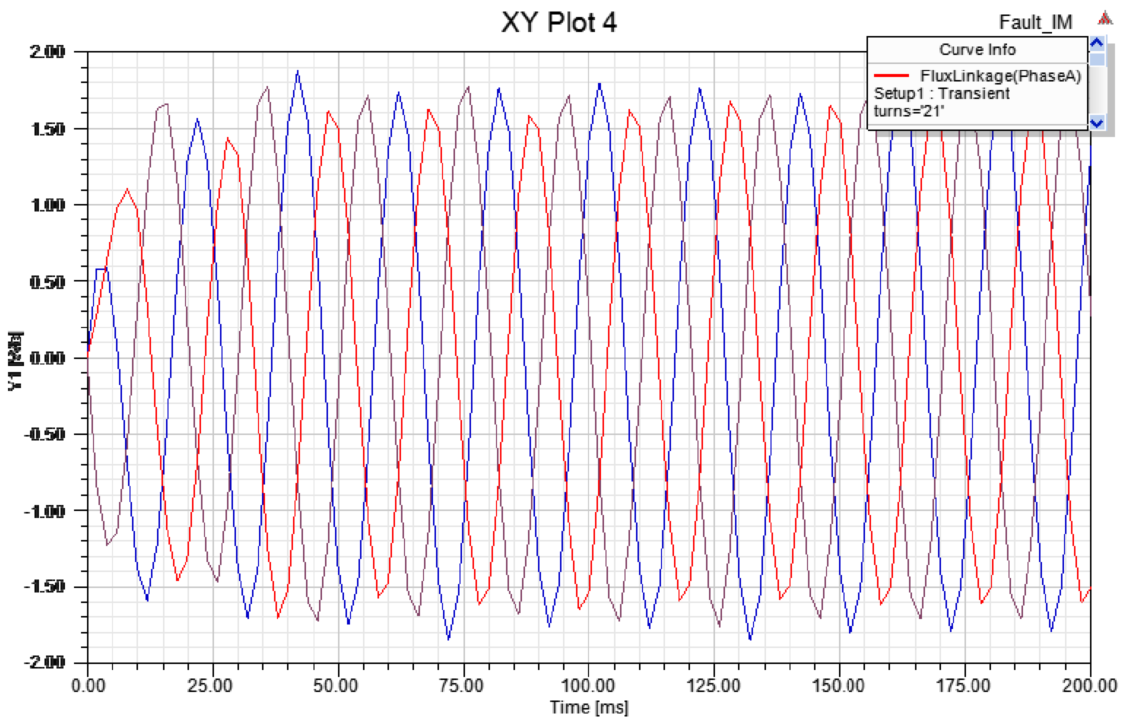

Figure 4.9: Flux linkages in faulty condition (5% turns short).

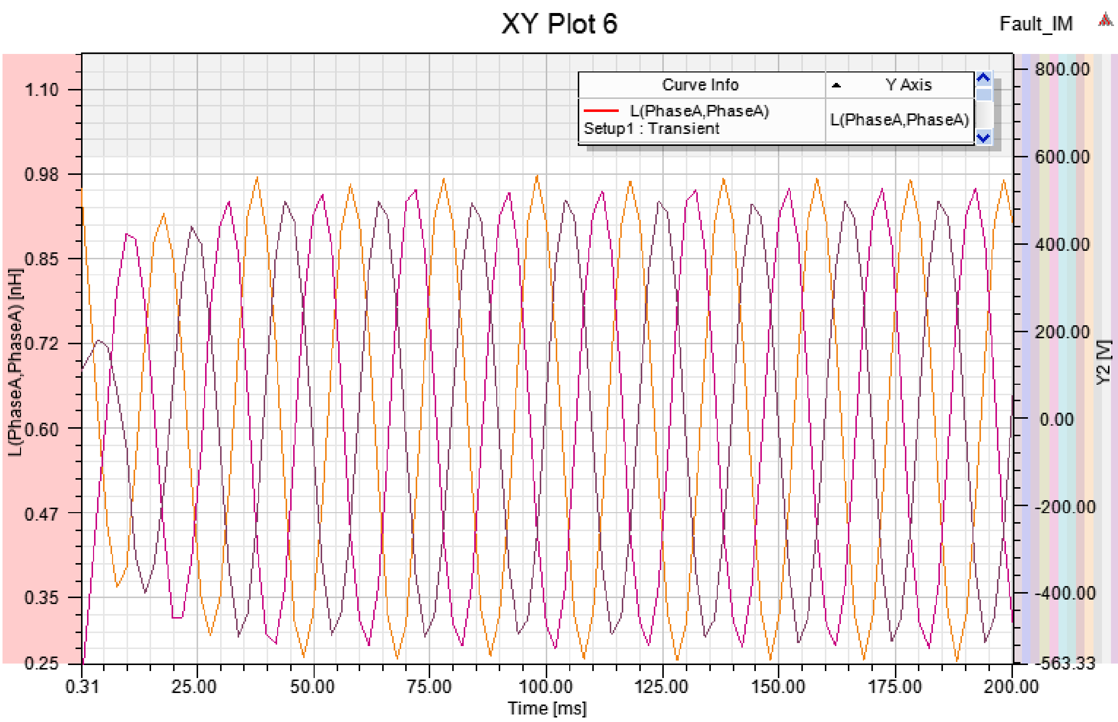

Figure 4.10: Stator currents in faulty condition (5% turns short).

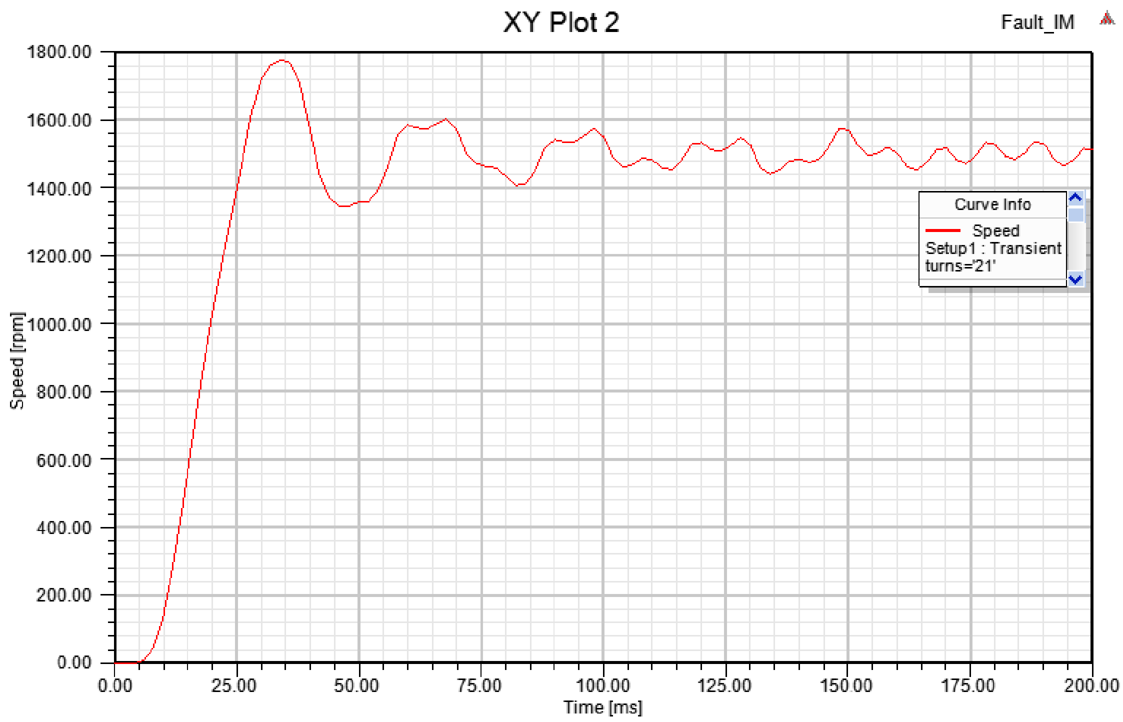

Figure 4.11: Speed profile of in faulty condition (5% turns short).

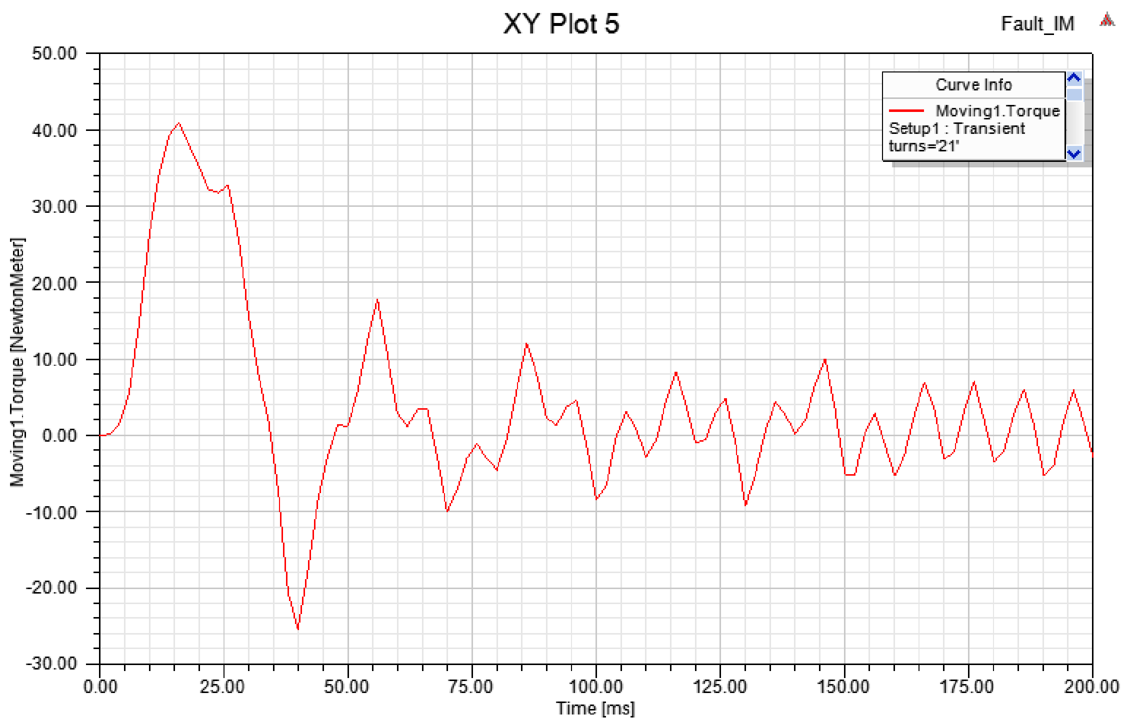

Figure 4.12: Torque profile of in faulty condition (5% turns short).

4.3 Experimental Set-up for Inter-turn Faults in Three Phase Induction Motor

In order to discriminate the healthy and faulty condition in real time experimental data are obtained from the induction motor of the specifications as shown in Table 4.1 and experimental test bed is shown in Figure 4.13. The inter-turn fault severity is considered as 5%, 10%, 15% and 20% of total turn short in phase A from the neutral point.Total number of conductor in phase A winding is 420 (4 coils/phase). I have taken only one coil having 105 turn in phase A of the stator winding for taking out the tappings (21,42,63,84 turns) have been short circuited for 5%, 10%, 15% and 20% short circuit condition.

Table 4.1: Parameters of IM for inter turn fault

Variable	**Value**
Rated Power	1 HP
Rated Voltage	440 V
Frequency	50 Hz
Rated Speed	440 rpm
Number of Pole	4
No. of turns per phase	420
Types of winding	Progressive
Connection type	Star
No. of stator slots	36
No. of rotor slots	28

The signature of the stator current have been taken from the current probe to 16 channel digital storage oscilloscope and analyzed by FFT. The Total Harmonic Distortion (THD) have been calculated in normal as well as in faulty condition as shown in figures below.

Figure 4.13: Experimental test bed.

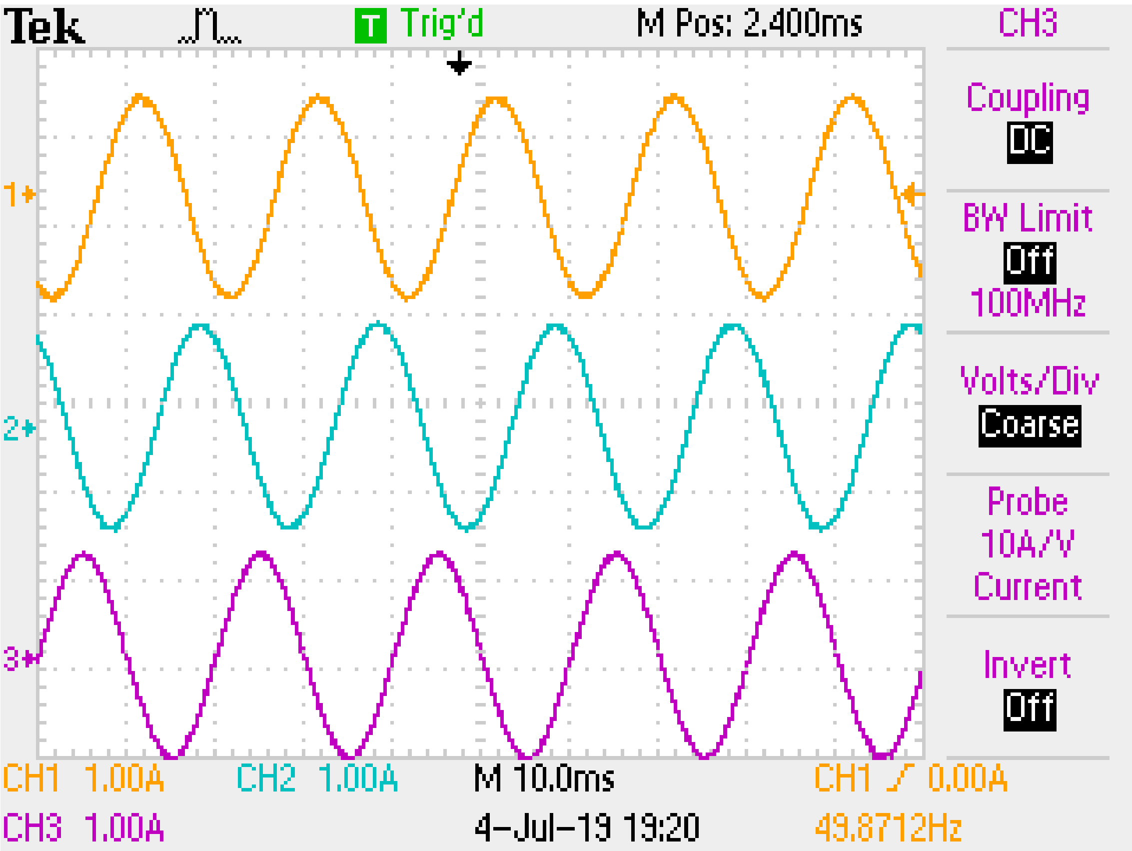

Figure 4.14: Stator currents in healthy condtion.

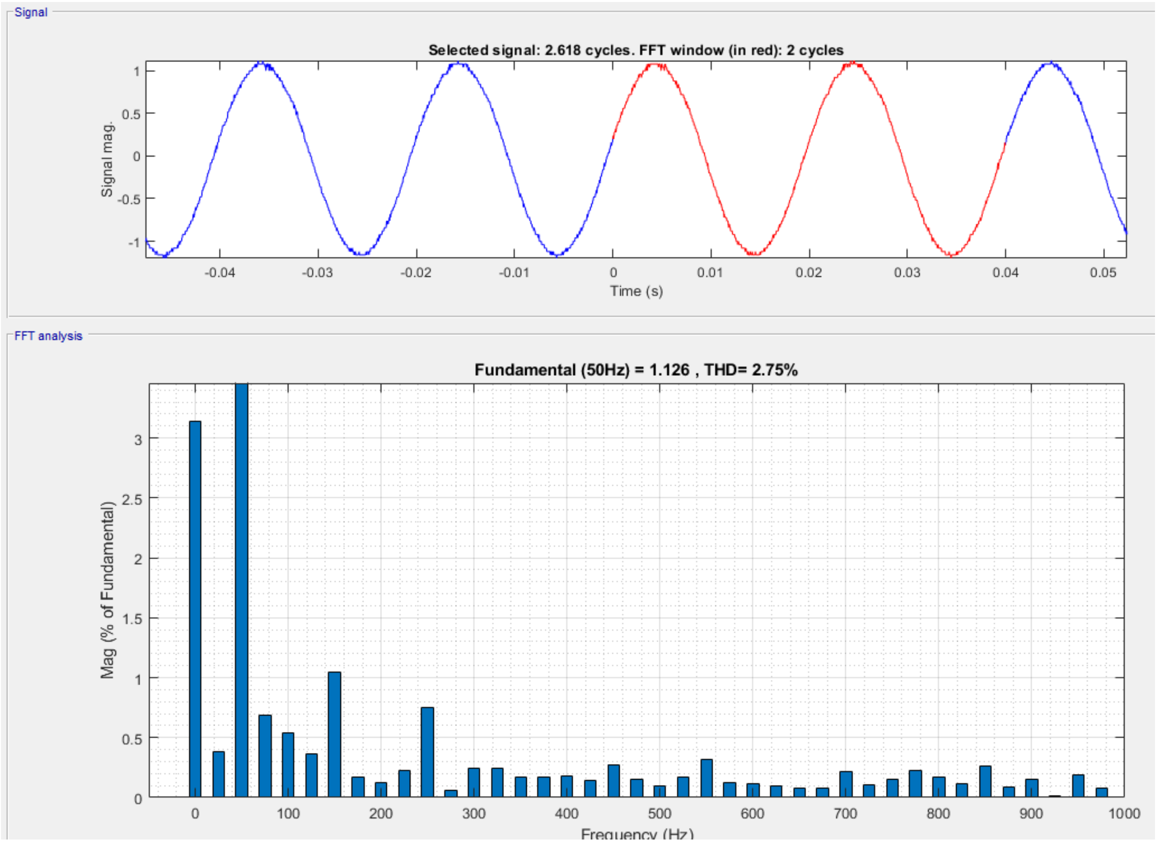

Figure 4.15: Current signal, FFT and THD of phase A under healthy condition

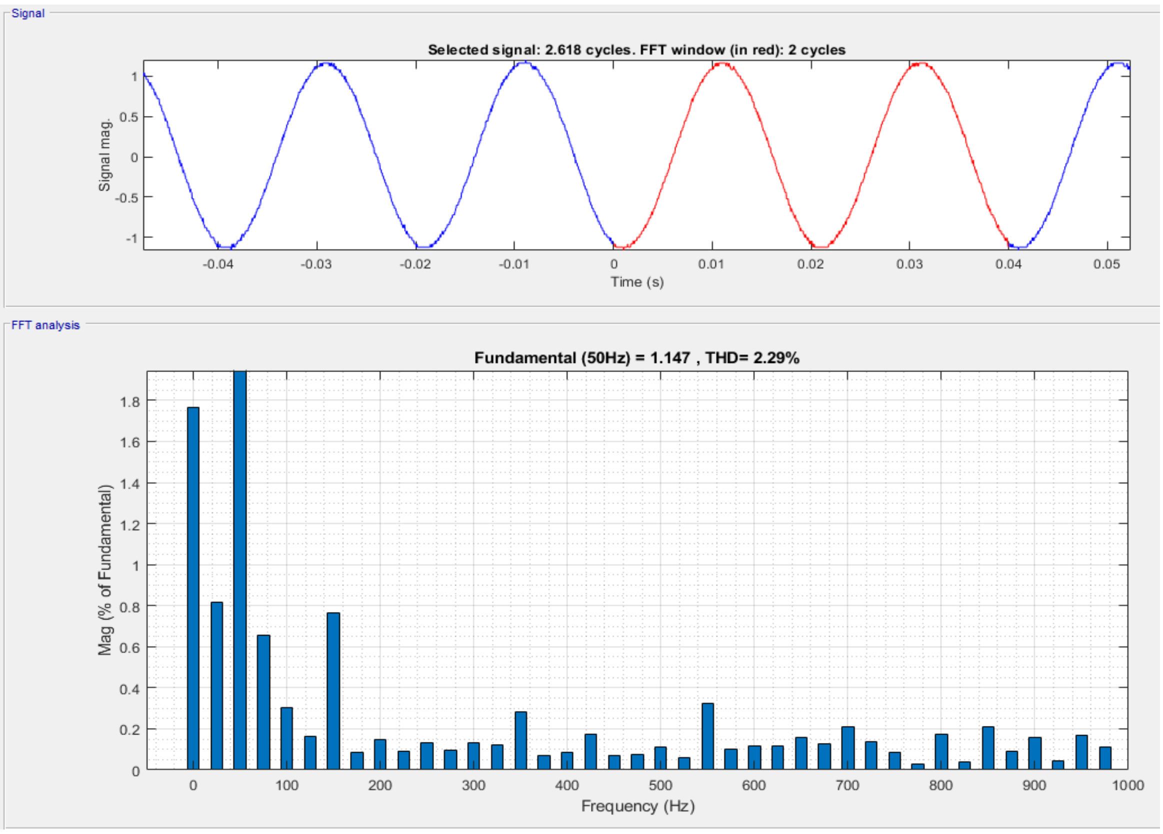

Figure 4.16: Current signal, FFT and THD of phase B under healthy condition

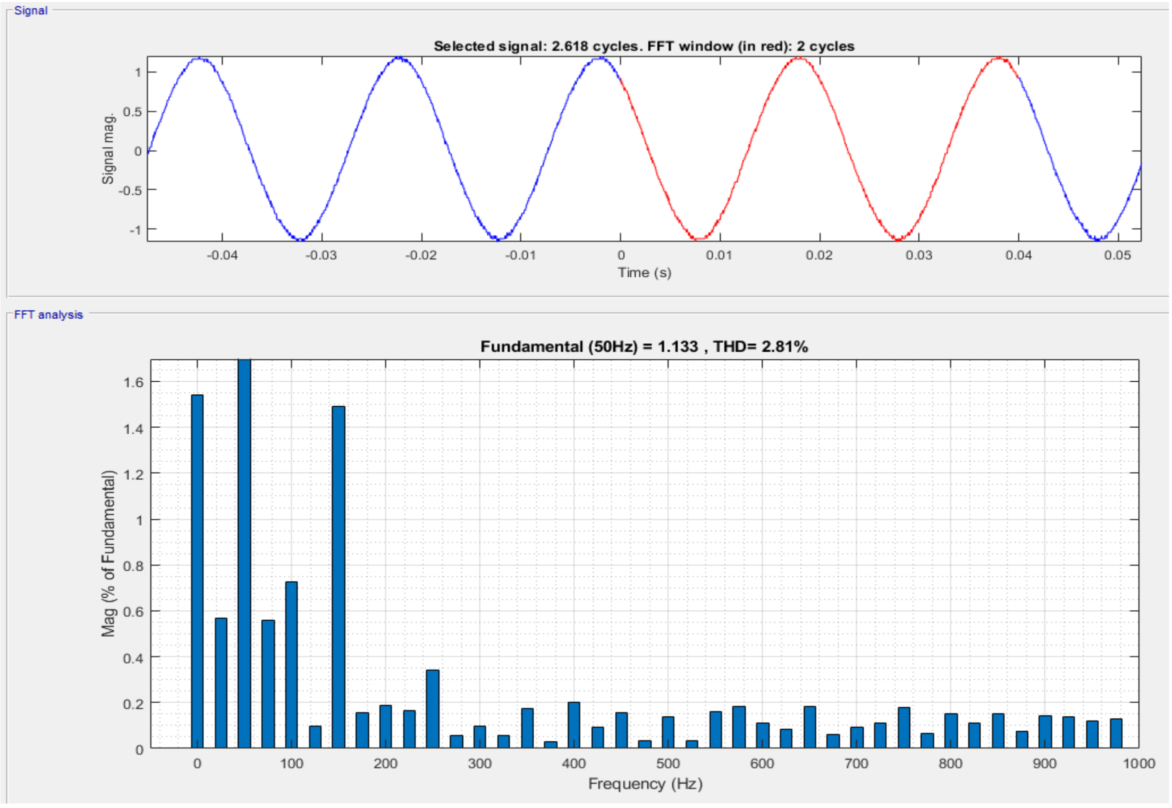

Figure 4.17: Current signal, FFT and THD of phase C under healthy condition

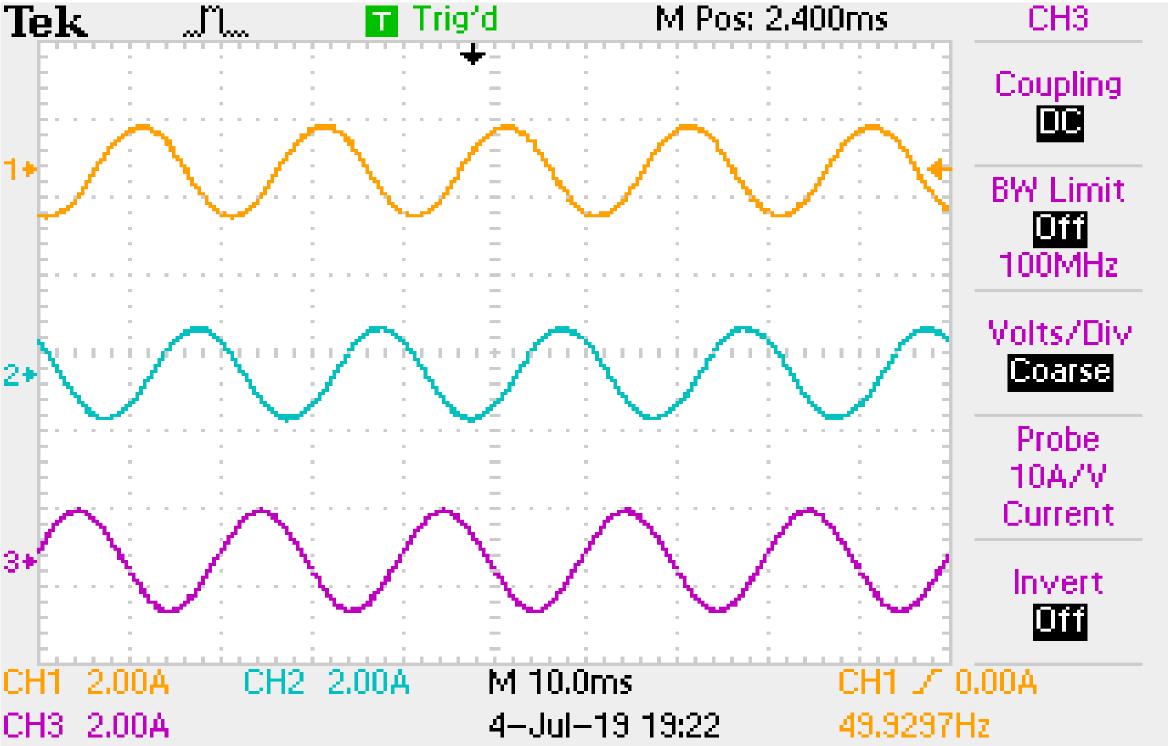

Figure 4.18: Stator currents under 5% short circuit condition.

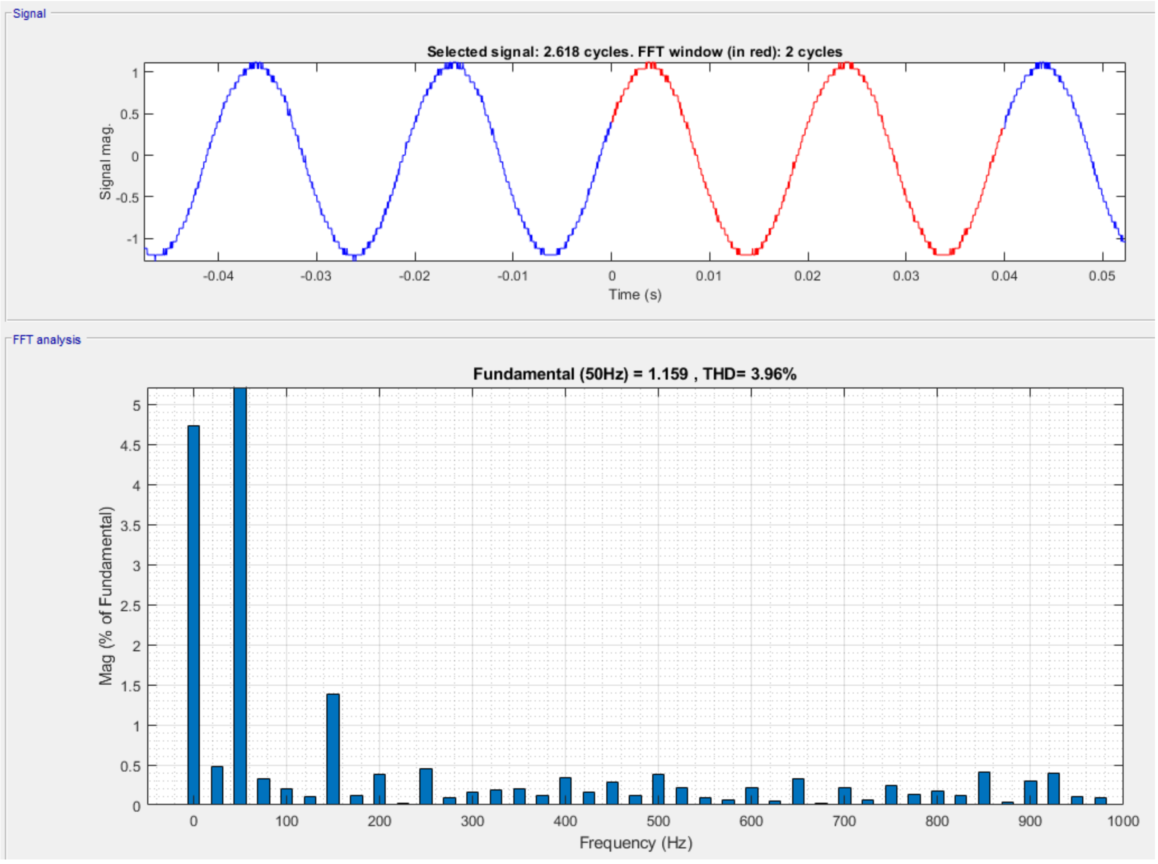

Figure 4.19: Current signal, FFT and THD of phase A under 5% faulty condition

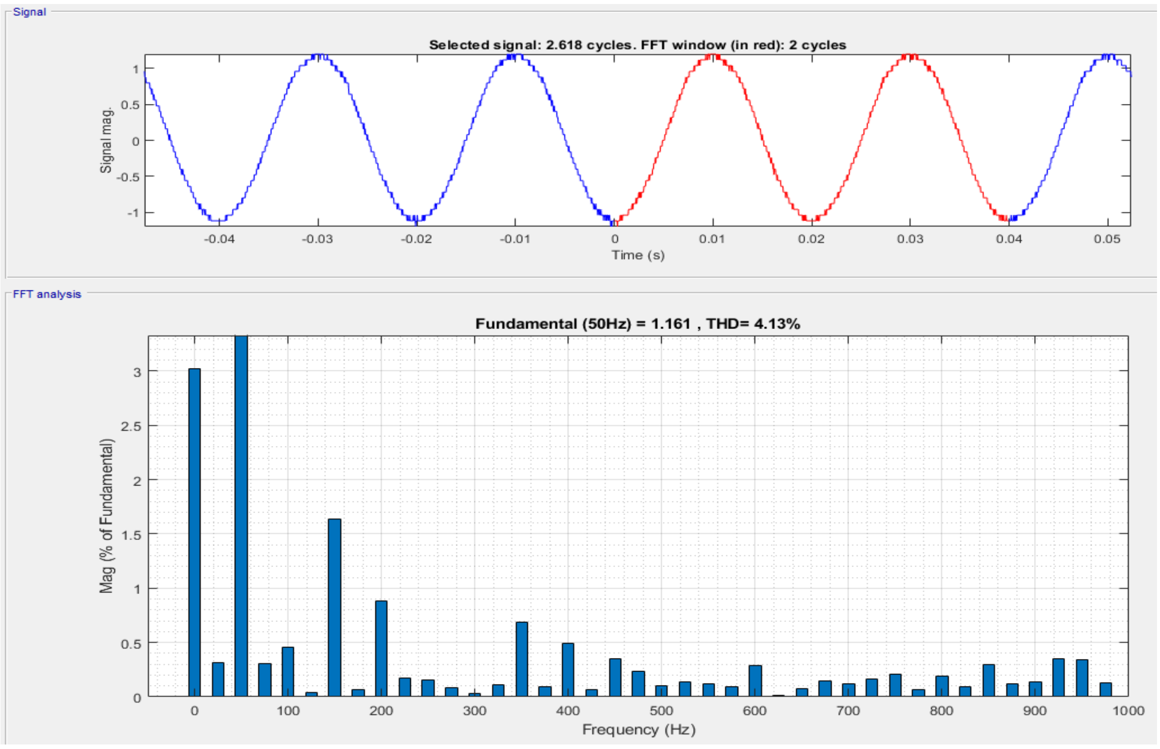

Figure 4.20: Current signal, FFT and THD of phase B under 5% faulty condition

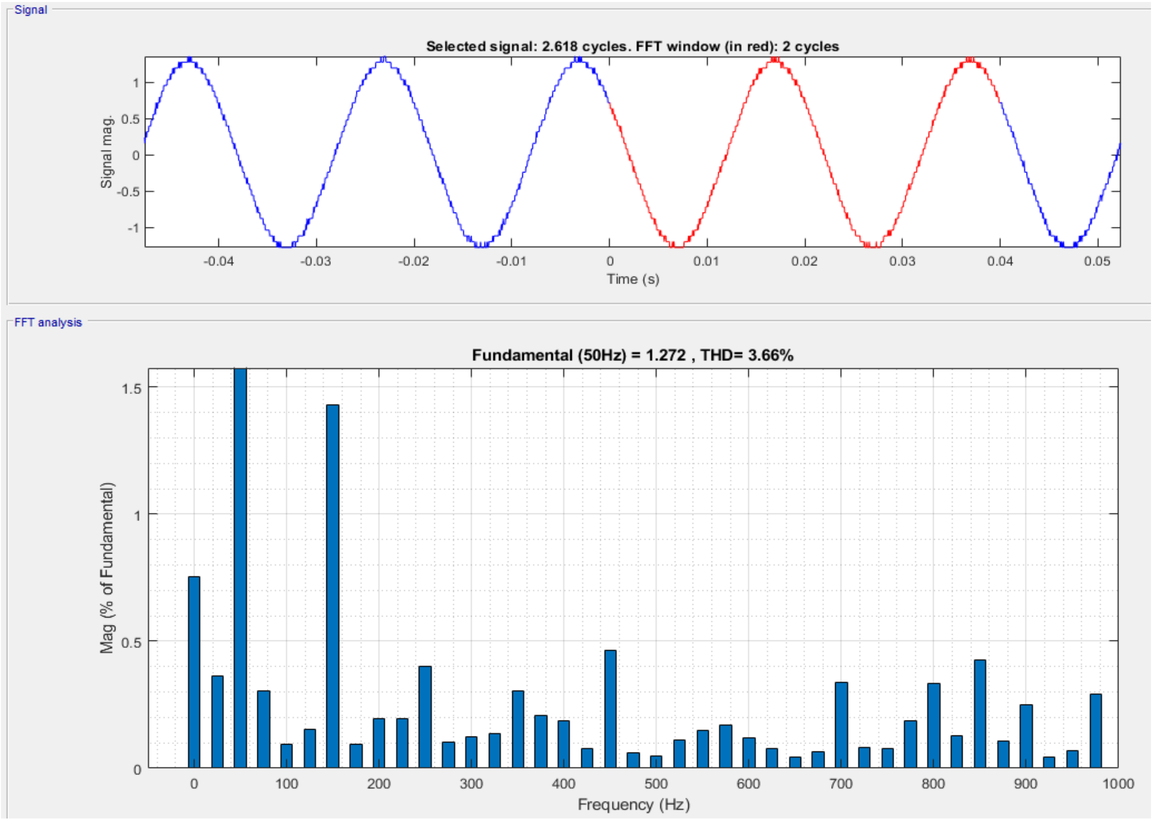

Figure 4.21: Current signal, FFT and THD of phase C under 5% faulty condition

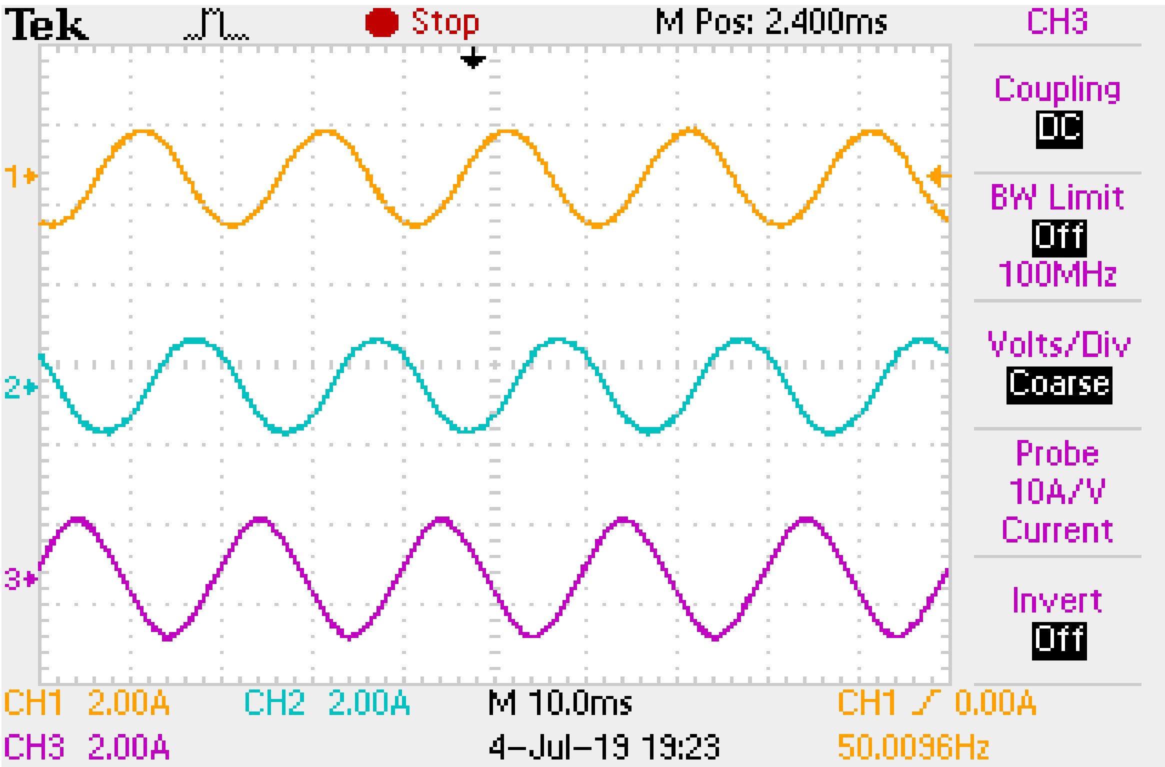

Figure 4.22: Stator currents under 10% short circuit condtion.

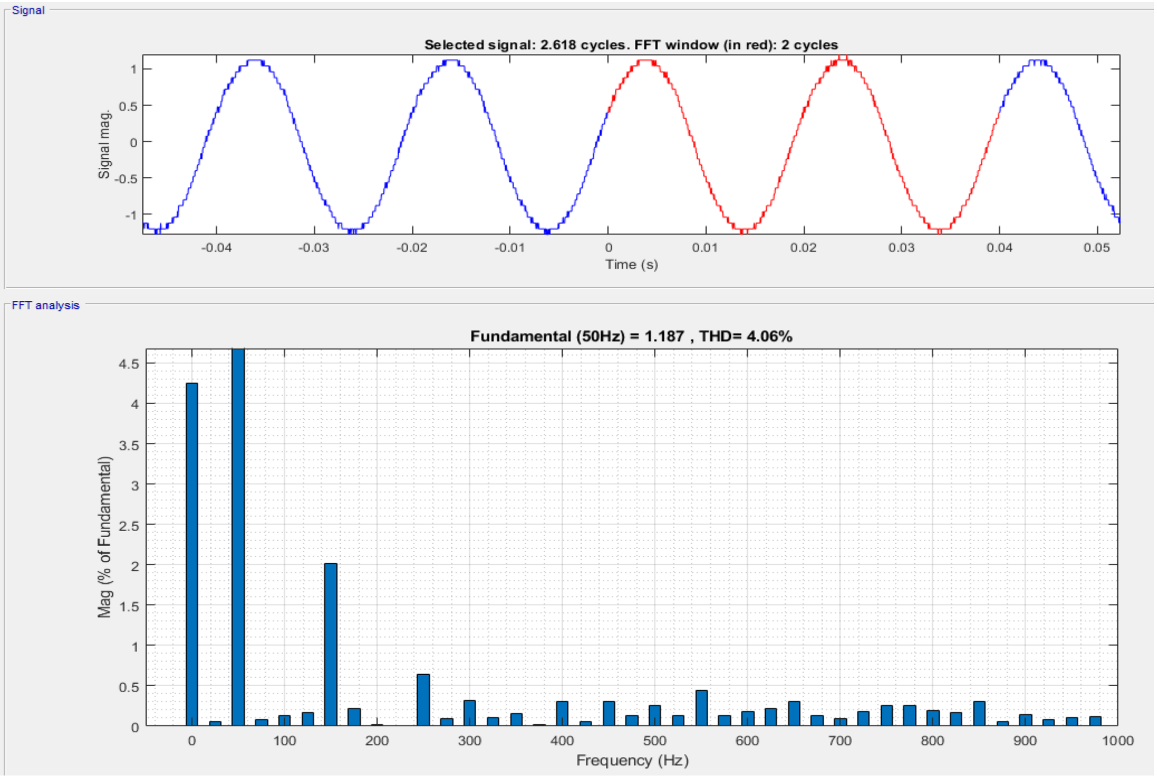

Figure 4.23: Current signal, FFT and THD of phase A under 10% faulty condition

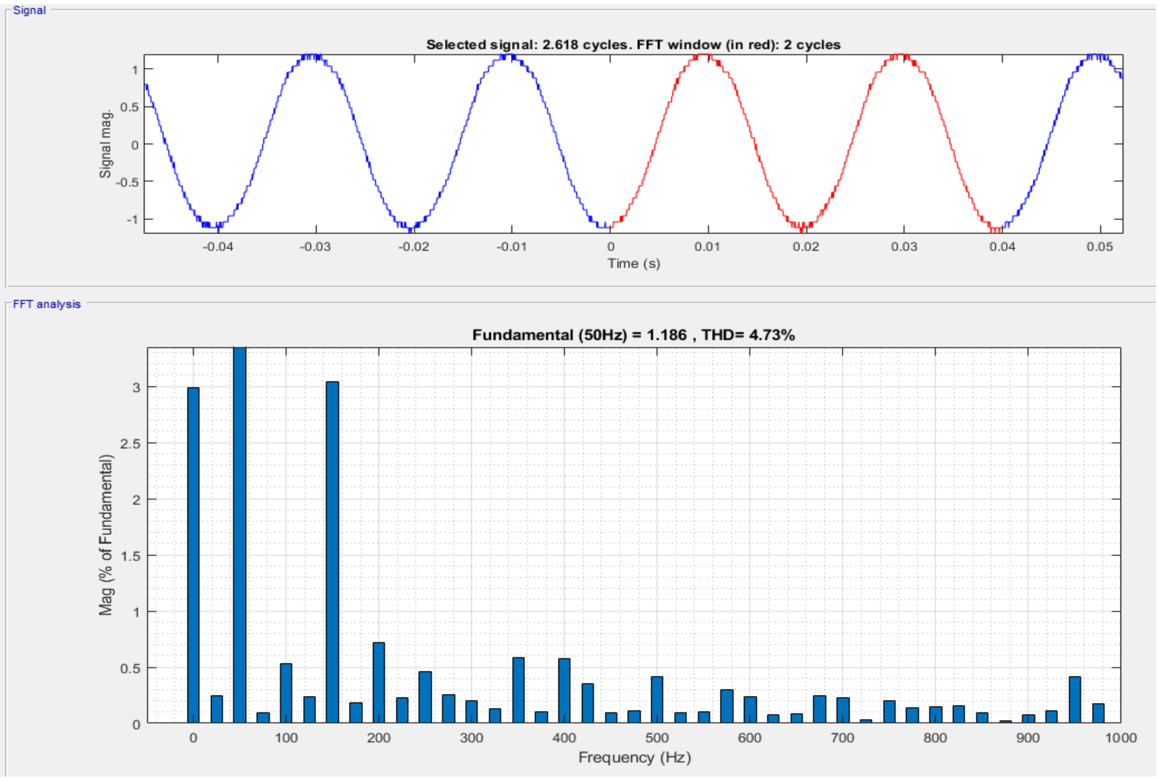

Figure 4.24: Current signal, FFT and THD of phase B under 10% faulty condition

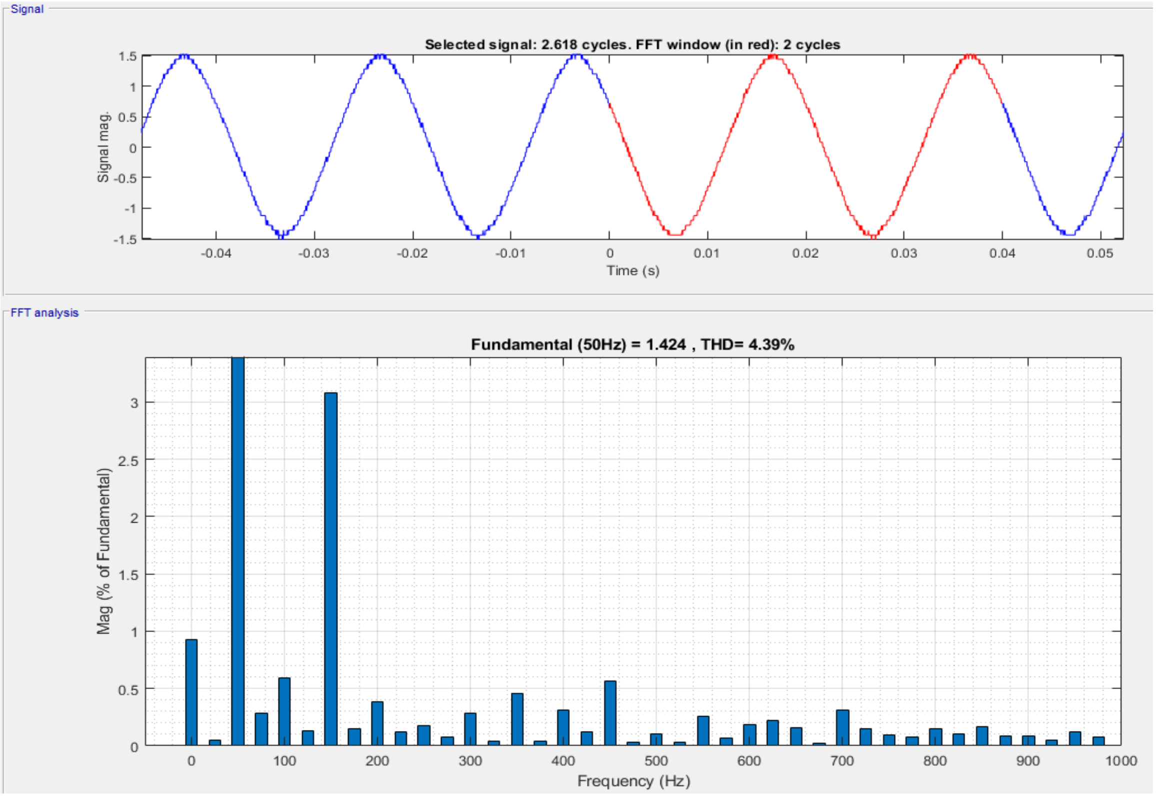

Figure 4.25: Current signal, FFT and THD of phase C under 10% faulty condition

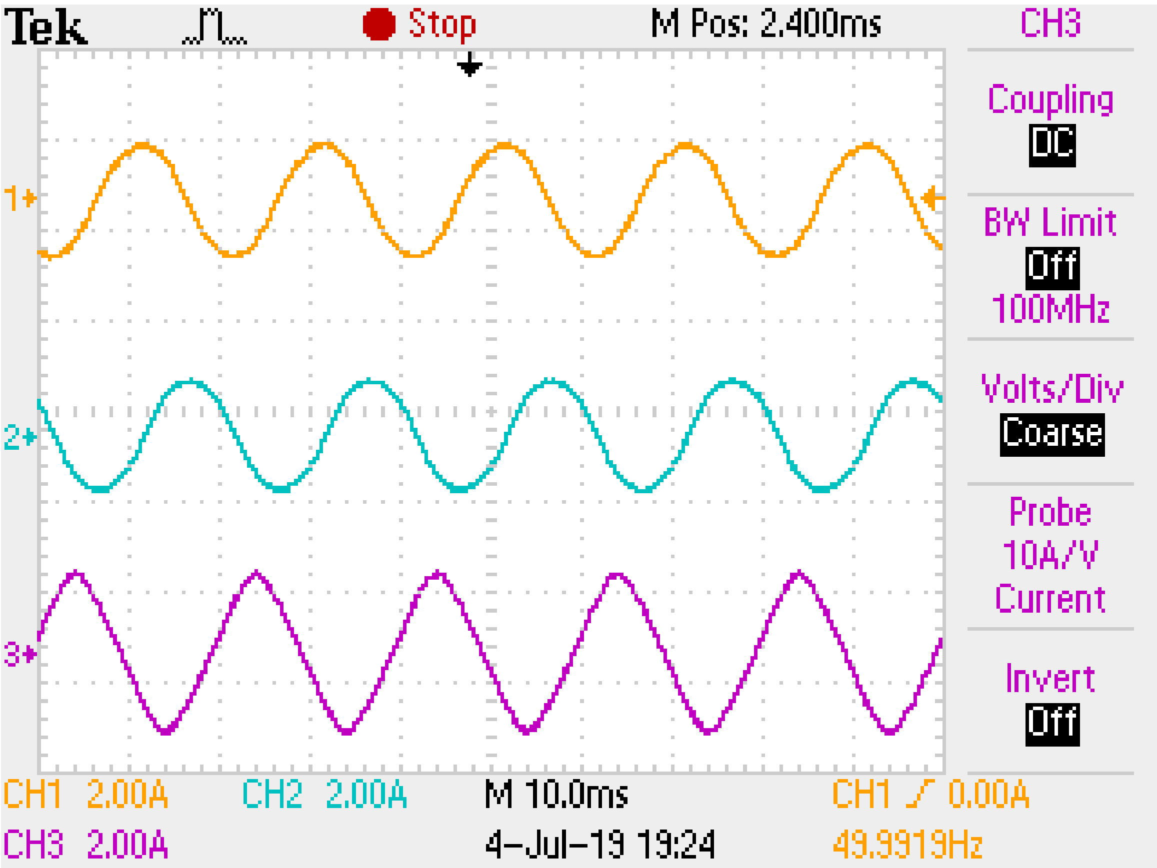

Figure 4.26: Stator currents under 15% short circuit condition.

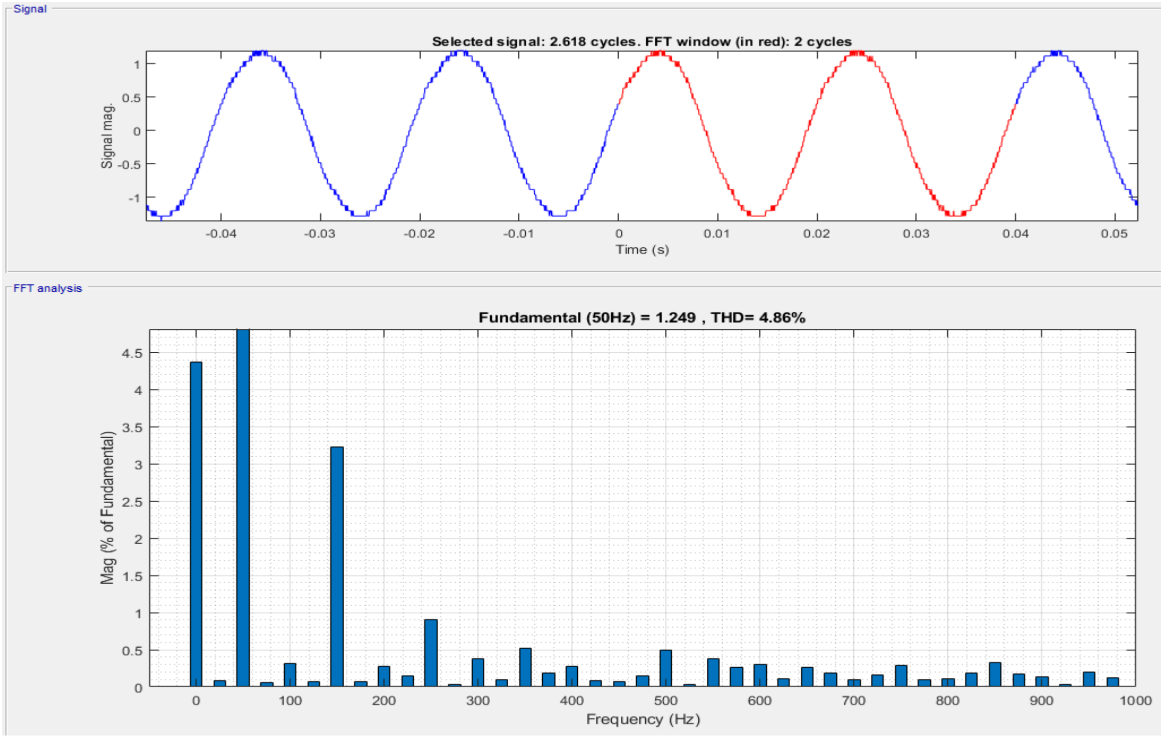

Figure 4.27: Current signal, FFT and THD of phase A under 15% faulty condition

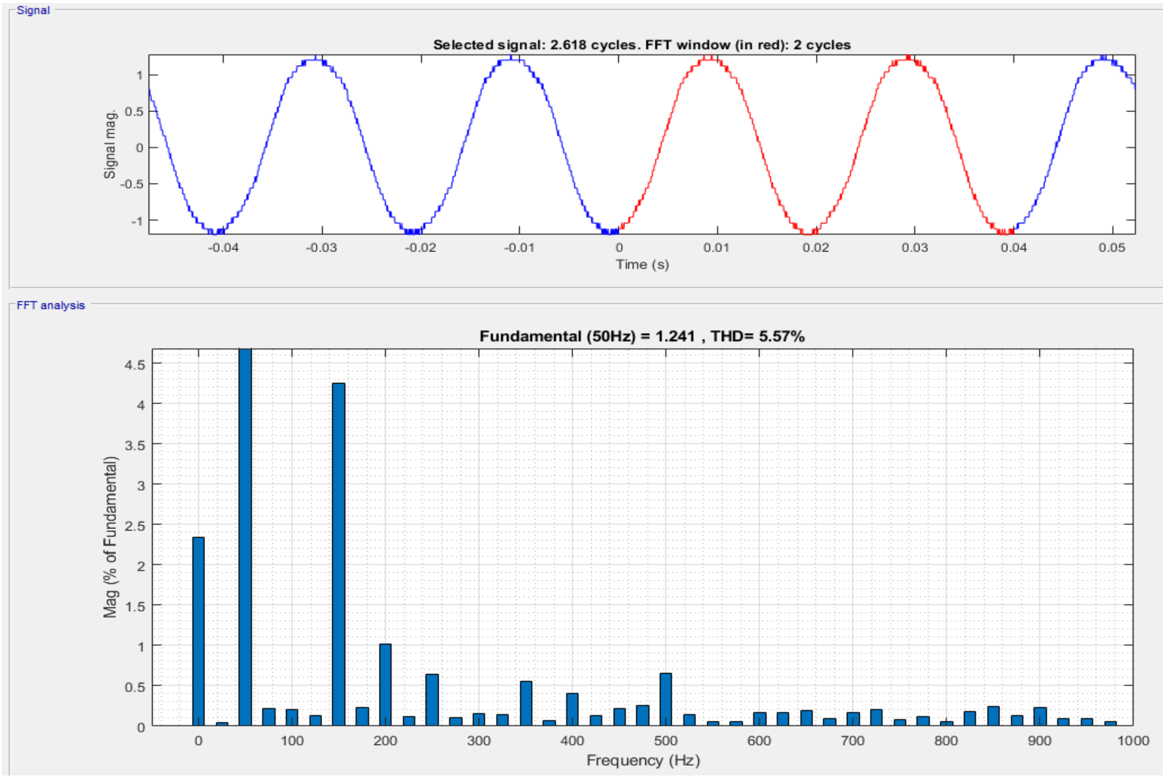

Figure 4.28: Current signal, FFT and THD of phase B under 15% faulty condition

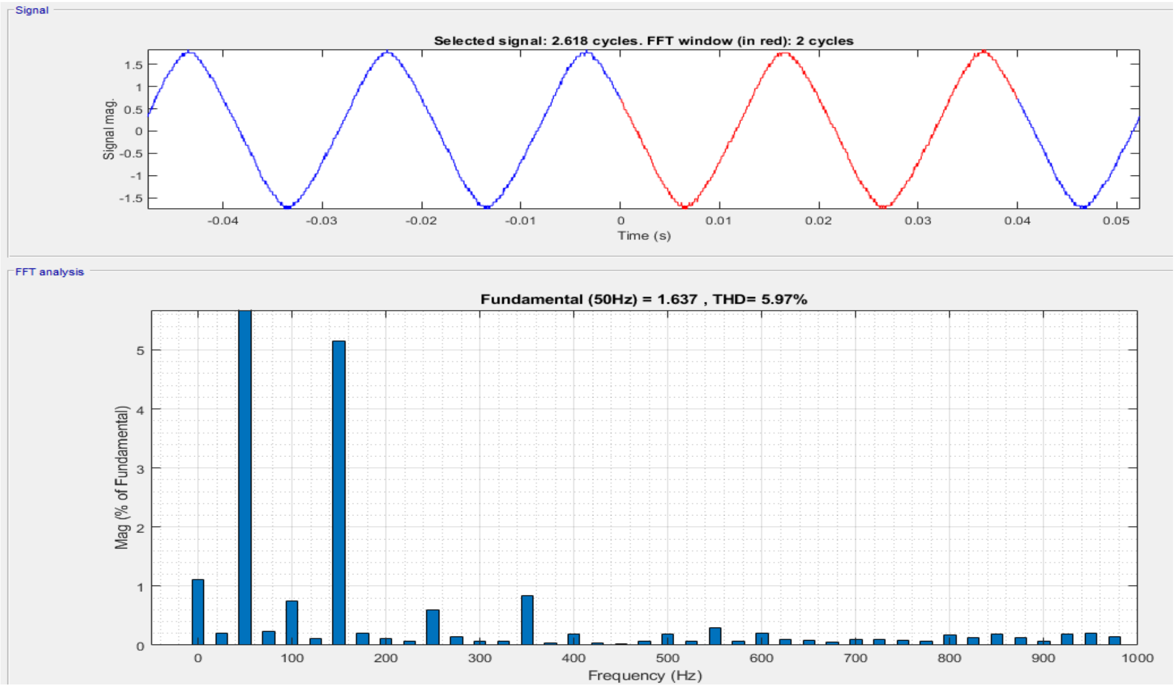

Figure 4.29: Current signal, FFT and THD of phase C under 15% faulty condition

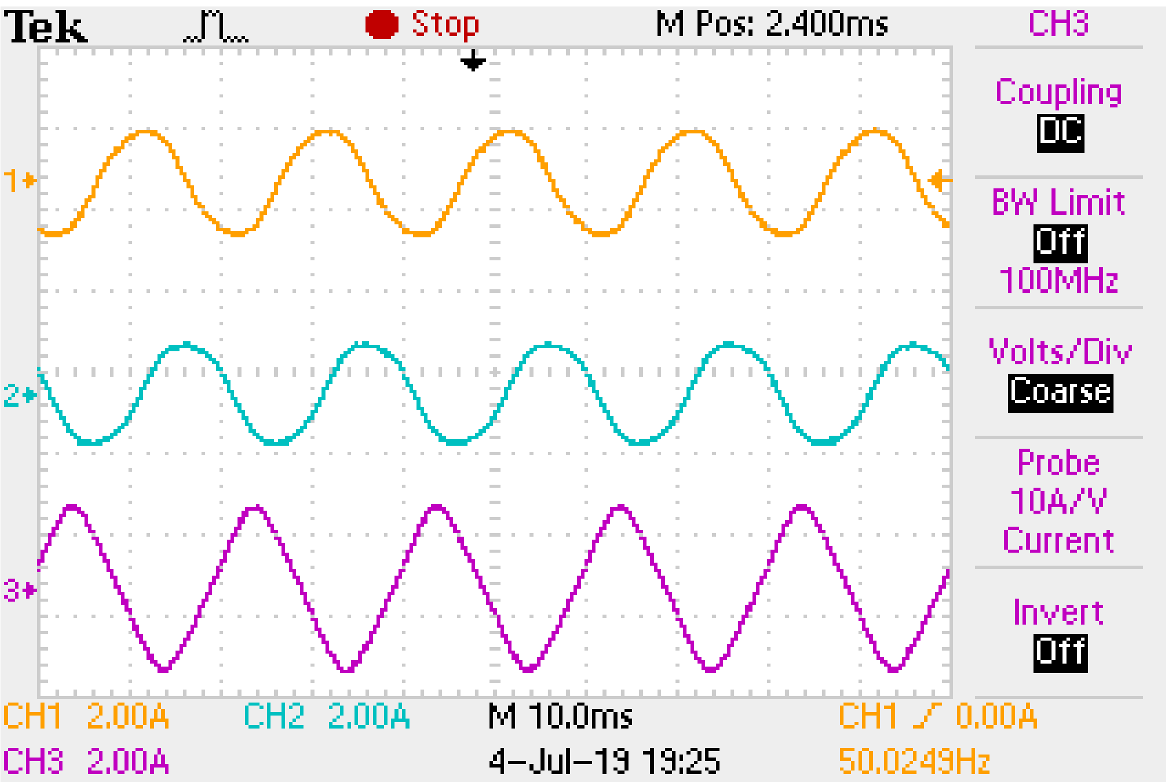

Figure 4.30: Stator currents under 20% short circuit condition.

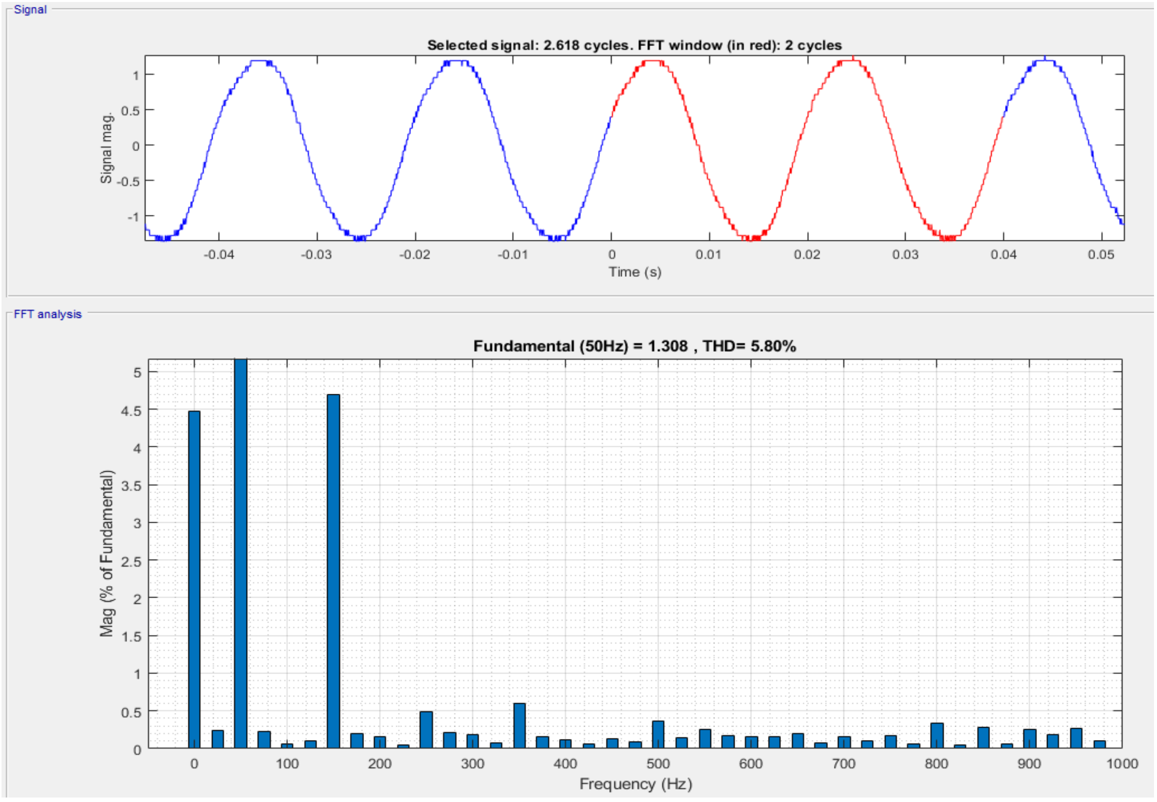

Figure 4.31: Current signal, FFT and THD of phase A under 20% faulty condition

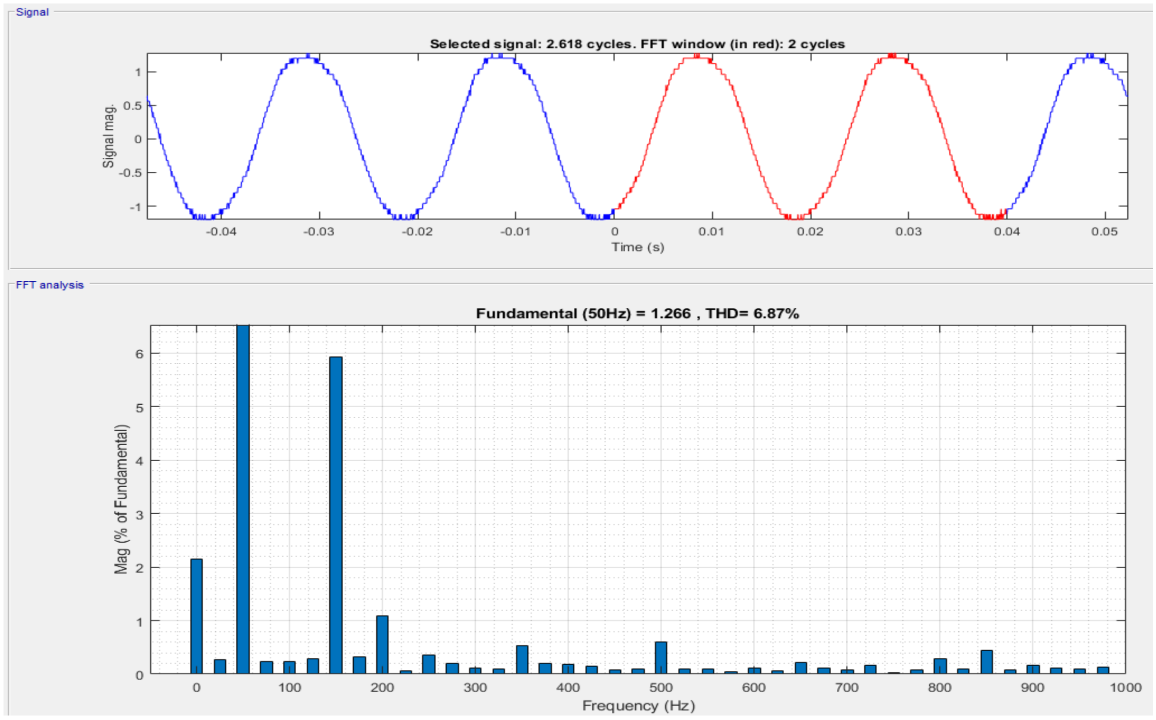

Figure 4.32: Current signal, FFT and THD of phase B under 20% faulty condition

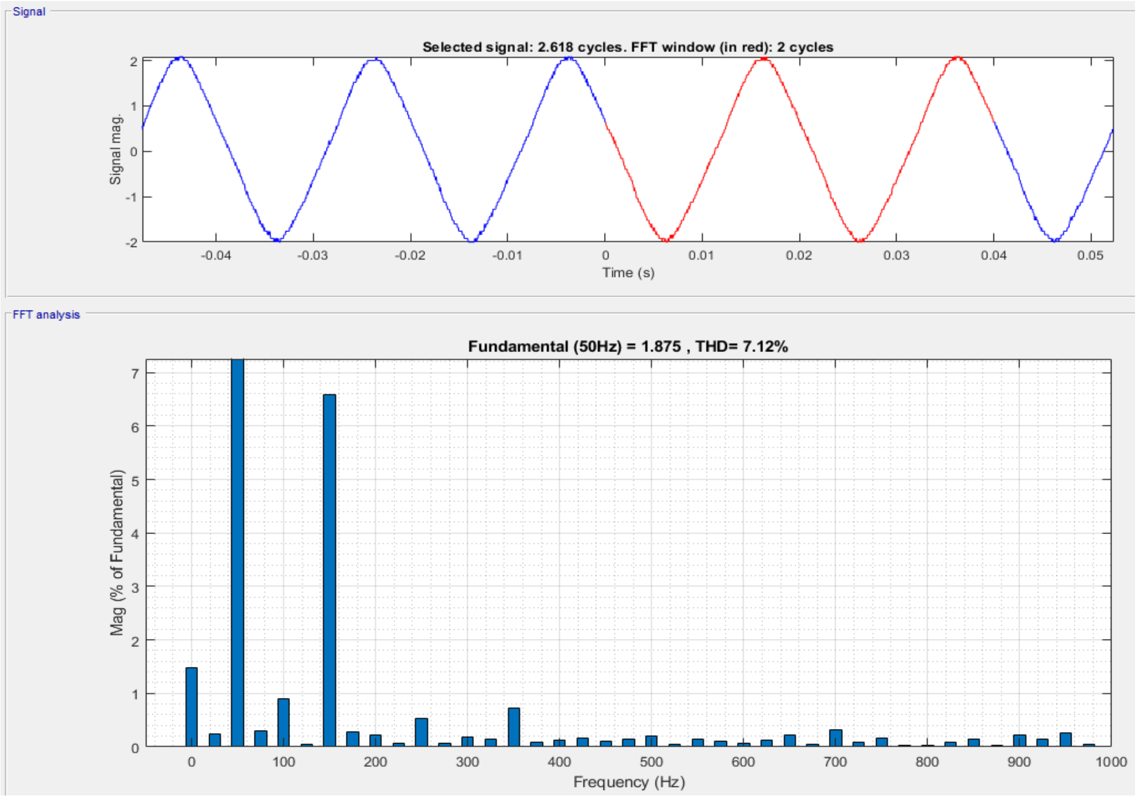

Figure 4.33: Current signal, FFT and THD of phase C under 20% faulty condition

4.4 Brief Explanation of Different Pattern Classification Schemes

4.4.1 ANN as a Pattern Classification Scheme

Artificial neural networks model is inspired from biological learning process of the human brain and have been developed in form of parallel distributed network. During the training process of the neural networks are fitted to the data by learning algorithms. In this work, supervised learning has used 70 % of training data and 30 % data used for testing. In this work, the traditional back propagation algorithm has been used which is regarded by the usage of a given out-put that compared to the predicted output and by adjusted of all parameters according to comparison. The parameters of ANNs such as weights are usually initialized with random values drawn from a standard normal distribution. The first step of the ANN training process is that to compute an output for given inputs and its current weights and output is compared with predicted output. The second step is to calculate the error and as per algorithm weights are adjusted and checked error below the threshold value. However, the training time is relatively long and it is also susceptible to local minimum traps [199, 200].

4.4.2 SVM as a Pattern Classification Scheme

The Support Vector Machine (SVM) in is a new kind of classifier that is motivated by two concepts. First, transforming data into a high-dimensional space can transform complex problems (with complex decision surfaces) into simpler problems that can use linear discriminant functions. Second, SVMs are motivated by the concept of training and using only those inputs that are near the decision surface since they provide the most information about the classification. It is a kind of learning machine based on statistical learning theory. The basic idea of applying SVM to pattern classification can be stated as follows: first map the input vectors into one features space, possible in higher space, either linearly or nonlinearly, which is relevant with the kernel function. Then, within the feature space from the first step, seek an optimized linear division, that is, construct a hyperplane which separates two classes. It can be extended to multi-class. SVMs training always seek a global optimized solution and avoid over fitting, so it has ability to deal with a large number of feature [201-203]. In this work, supervised learning has used 70 % of training data and 30% data used for testing by using RBF kernel.

4.4.3 Classification of signals by ANN and SVM

For fault classification the samples of stator currents at different faults as well as loading conditions has been taken. Total number of features for training was 80 and 20 for testing, 10 samples of the signal after being normalized was taken as input vectors for proper feature selection.

The feed forward artificial neural network (ANN) with back propagation algorithm has been adopted for classification of faults. The acceleration factor, learning rate and momentum is choosen 0.2, 0.1 & 0.8 respectively. After 65 iteraition error curve converges which indicates proper freezing of the weights. Once the neural network is trained out of the 80 datasets with 100 datasets available, the efficacy of the algorithm is tested for the remaining 20 datasets and the classification accuracy is obtained as 87.26 %. Similarly the support vector machine (SVM) is implemented according to Kuhan-Tucker condition. Here the regulation parameters and the slack variable is choosen as 0.2 and 0.8 respectively. In the higher dimensional feature space, the fault and no fault situation is clearly discriminated with minimum overlapping class. The classification accuracy is obtained is 93.21% which is superior than that of ANN.

4.5 Result & Discussion

In the steady state the current signal from the hardware setup is shown in a 16 channel CRO which indicates the clear phenomenon of steady state scenario further the tapping at 5%, 10%, 15% and 20% are created and corresponding signal is retrieved subjected to short at a particular phase thus, the signal retrieved after the short circuit indicates the fault scenario and the corresponding FFT analysis is done to evaluate the harmonic content of the signal by means THD. It is important to discriminate the fault with that of the steady state scenario. Thus the intelligent pattern classification scheme such as ANN, SVM was considered for subsequent classification of the fault.

4.6 Conclusion

This chapter discusses the classification scheme by means of ANN and SVM to discriminate fault condition with that of no fault condition. The experimental prototype has developed in electrical machine lab and subsequent signal was retrieved for classification objective. The accuracy of the obtained results clearly indicates the discrimination between the fault and no-fault condition. Further the reliability is an important aspect for the condition monitoring objective is discussed in subsequent chapter.