Low Severity Inter Turn Short Circuit Fault Diagnosis in Permanent Magnet Synchronous Motors Using Machine Learning

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Copyright Declaration

The thesis titled **“Low Severity Inter-Turn Short Circuit Fault Diagnosis in Permanent Magnet Synchronous Motors Using Machine Learning”** is submitted in partial fulfillment of the requirements for the degree of **Master of Engineering (M.Engg)** in **Electrical and Electronic Engineering (EEE)** at **Chittagong University of Engineering and Technology (CUET).** This research has been carried out under the **CARE project (NORPART-2021/10355)**, a collaborative initiative between Chittagong University of Engineering and Technology (CUET), Chattogram-4349, Bangladesh, and the University of Agder (UiA), Grimstad-4879, Norway.

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Signature of the author

Preface

This Master's thesis is carried out at the University of Agder, Grimstad Campus, Norway. This thesis is written in the Autumn 2023 semester. The support is carried out by the collaborative CARE project NORPART-2021/10355 between Chittagong University of Engineering and Technology (CUET), Chattogram-4349, Bangladesh, and the University of Agder (UiA), Grimsted-4879, Norway. While doing this study, I have learned so many things including theoretical knowledge in multiple fault analysis of rotary machines and their detection strategy and so on. That enriched me in the knowledge domain and gave me a lifelong experience.

I am thankful to many people who gave me enormous support during this journey. Firstly, I would like to express my heartfelt gratitude to my honorable Prof. van Khang Huynh for giving me the right detection from the very beginning. He helps guide me to reach my ultimate destination to fulfill all requirements for my thesis. Also, I want to be grateful to two Ph.D. scholarship holders Thien Phuoc Nguyen and Hoang Nam du Nguyen of UiA for giving me the directional path about methodology and also answering my endless questions about this work. Their follow-up and recommendations keep me on track to fulfill my objectives. Without the support of those people, I may not able to complete my task in a very short time frame while making my appearance in Norway was late due to visa issues.

I want to express my thanks to my home institution supervisor Dr. Sampad Ghosh for motivating me to join this program and make this journey remarkable. Also special thanks to my friends who are here in Norway for giving me company at my tough time in this new environment.

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***Abstract*—The study represents the diagnosis of the low-severity inter turn short circuit (ITSC) fault in the permanent magnet synchronous motors (PMSMs). A pre-recorded in-house three-phase current data is used to distinguish between the healthy, 2% ITSC, and 5% ITSC fault detection in the stator winding at a fixed speed and load. This analysis is targeted at condition monitoring and predictive maintenance of the system. The supervised machine learning techniques take recorded time series of three-phase current data as a key ingredient for classification. Specifically, four supervised machine learning (ML) algorithms decision tree (DT), random forest (RF), extreme gradient boosting (XGB), and support vector machine (SVM) are used to evaluate the performance of the classification for different fault severity level with the healthy condition. For this classification, statistical features like crest, impulse, kurtosis, etc. factors with a total of 9 other statistical features are determined to serve the purpose. Wrapper-based feature selection (WFS) technique is employed for finding the optimal subset of features to get the maximum accuracy while reducing computational complexity using the mentioned supervised machine learning algorithms. It is vital to note that the combination of root mean square (RMS) factor, standard deviation factor, and crest factor is the optimal performing feature for both classifications between healthy to 2% ITSC and healthy to 5% ITSC fault with the accuracy percentage of around 85% and 98.33% in level 3 of SVM algorithm.**

Keywords—Fault, Classification, Features, Algorithms

I. INTRODUCTION

In modern days, permanent magnet synchronous machines are a great alternative for wind or offshore wind applications where monitoring and maintenance are logistically difficult and expensive [1]. PMSMs, or permanent magnet synchronous motors are a well-known component of many commercial and industrial applications, including wind turbines and electric cars, etc. Even though they are comparatively expensive, their great efficiency, simplicity of control, and large torque-to-size ratio make them widely used [2-3]. Other main advantages of PMSMs are their higher power factor and longer lifespan compared to other competitive machines. However, several challenges are laid in the background to ensure a smooth and cost-effective operation. Thus, its operational challenges including fault diagnosis, maintenance, etc. are always a well-established research field among the scientific communities.

PMSMs are generally used in industries with many environmental challenges including thermal, mechanical, and electrical stress. Those factors are the main culprits for occurring several faults like mechanical, electrical, and magnetic faults. In electrical faults, there are basic three categories specifically inter-phase fault, inter-turn fault, and phase-to-ground fault [4]. Inter turn short circuit (ITSC) is one of the regular and dangerous types faults among of electrical faults which contain almost 21% of short circuit faults in electric motors [5-6]. Insulation from the windings has deteriorated which leads to making a short path between the coils. For this reason, a fault resistance is introduced and the current flow deviates from the nominal rating. Consequently, the unbalance of the current flow has produced excessive heat in the coil and made a partial demagnetization of the magnets [7]. That phenomenon has greatly reduced the performance and the efficiency of a PMSM. Also, substantial faults may lead to the complete failure of the machine. Hence, it is recommended to detect this fault in the early stage to reduce the economic loss and any unwanted shutdown of a system. There are some popular techniques for analyzing the faults of PMSMs. Motor current signal analysis (MCSA) and zero sequence voltage component (ZSVC) are the two most used analysis techniques. MCSA can detect the ITSC fault in the PMSMs and is effectively used with data of higher sampling rates [8]. MCSA is a handy tool for looking after the health, efficiency, and overall performance of any rotating machine.

Three established common types of fault diagnosis methods are model-driven, signal-based analysis, and data-driven methods [9]. Typically, the model-based one implements an analytical model to explain the typical behavior of the system. It also creates diagnostic algorithms to check the compatibility between the actual outputs of the real system and the expected outputs of the model [10]. The model-based one is faster but developing a reliable, accurate model and their corresponding parameters are the main bottleneck for the fault detection of a real-time system. The signal-based method has made the diagnosis based on the signals e.g., temperature, vibration, current, etc. for different categorical faults with real-time indicators obtained through feature extraction. Freire, N. M. et. al [11] focused on the identification of current sensor faults in permanent magnet synchronous generators (PMSGs) used in wind energy conversion systems. This approach is capable of detecting only the faulty phase of the sensor, but it is unable to determine the specific category like an open circuit, saturation, noise, etc. type of sensor faults. Lastly, the data-driven model contains the acquisition of relevant information, the extraction of features, and making use of machine learning algorithms to identify patterns associated with both healthy and faulty conditions of a complex system. However, the necessity of large amounts of historical data is one of the main challenges to developing an efficient data-driven model.

These models accurately capture the complicated behavior of complex systems, which would be harder to represent using a model-based method. The combination of machine learning algorithms besides data-driven models has made a revolutionary improvement in the fault diagnosis of real-time systems. Gyftakis, K. N. et. al. [12] introduced a technique of frequency spectrum analysis for the detection of ITSC at lower levels with MCSA from experimental data. However, the method is reported as an unreliable source for low-severity ITSC detection only with frequency spectrum analysis at the same time. Also, Lundgren, A. et. al. [13] provided a framework based on the data-driven model for the fault identification of technical systems and time-series data. The method is capable of handling unbalanced training data and detecting unidentified faults as well. To sum up, MCSA with a data-driven model may be considered as a potential tool for fault detection.

In this work, the main target is to diagnose low-severity ITSC faults with MCSA-based data-driven models in corporations with supervised machine learning (ML) algorithms associated with recorded time series current data by wrapper-based feature selection (WFS). Wrapper-based feature selection is a technique performed to identify the most relevant subset of features for machine learning algorithms. This approach assesses the efficacy of various feature subsets by employing a model. Commonly used wrapper approaches include backward elimination, forward selection, and recursive feature removal. Wrapper approaches have the benefit of considering the interaction between features, allowing them to capture the complex relationships present in the data. Nevertheless, they require significant computing resources and can lead to overfitting when dealing with a high number of features but this can be mitigated with optimal feature selection [14]. The classification is performed between healthy and faulty conditions and checks the performance with the four supervised machine learning algorithms which are decision tree (DT), random forest (RF), extreme gradient boosting (XGB), and support vector machine (SVM). Finally, the optimal features subset is identified with the most suitable features to identify the healthy and different faulty conditions while maintaining the best amount of accuracy.

The paper is outlined as: section II has presented a data overview with the specification and preprocessing of the used data in this study. After that, sections III, and IV discuss the procedures of fault diagnosis and the result of classification accuracy with machine learning accordingly. Lastly, section V has been followed by the conclusion of this study.

II. Data Overview

A. Data specification:

In this study, in-house experimental historical data of Ref. [2] is adopted. This setup has collected many sets of data with different faulty conditions like demagnetization and ITSC. Only three-phase current data is used in this study for detecting the various low-severity ITSC faults. The data is recorded with the help of current sensors, Microlabbox, and a computer setup at a sampling rate of 10kHz. Fig.1 shows the setup overview of the data recording process. The configuration consists of a power source and an ABB drive for the supply of the proper input for the PMSM. Current sensors are connected to the Microlabbox and record the data in the computer memory. The PMSM has an output power rating of 3 kW, 3000 rpm, and 2 pole pair with a nominal voltage and current of 315V, and 6A respectively. Loading condition is considered as 75% of the full load in this case. ITSC faults are developed by the wiring of the external taps applied in the PMSM with a different severity level of 2% and 5% of the total winding for a particular phase. The total number of data is obtained for 200 seconds where the individual phase contains 2000000 data points in the time domain for both healthy and faulty cases. Those data are considered the main computational ingredient to classify the healthy and the faulty conditions. The other specification of the data can be found in Ref. [2].

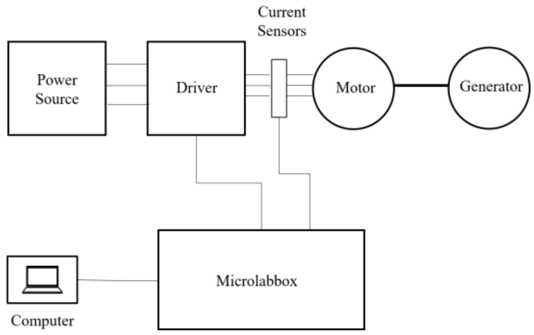


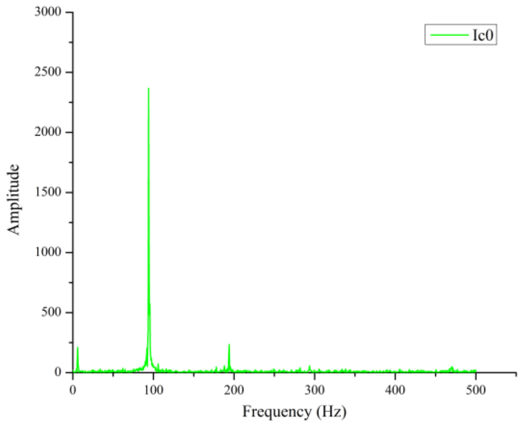
Fig.1 Data acquisition setup overview [2].

B. Data Preprocessing:

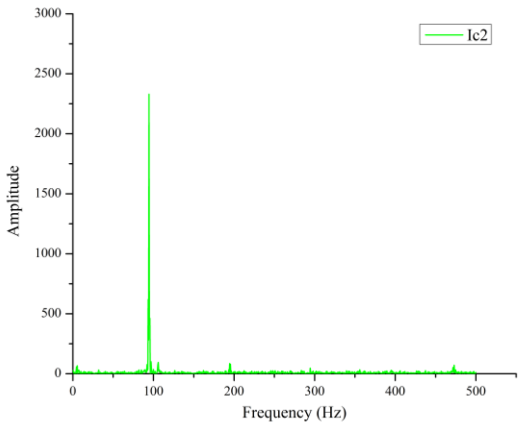
The raw data is captured with the help of the MATLAB software platform. From the raw data, processed data is wanted to extract features for classification. Initially, the data set is filtered with the Butterworth low pass infinite impulse response (IIR) with a filter order of 12, and a cut-off frequency is set to 0.5 times of Nyquist frequency which is eventually half of the sampling frequency. This kind of filter is chosen because of getting a smooth roll-off in the high-frequency region. Another purpose is the attenuation of the higher frequency component and allowing only lower frequency components from any raw signal. Butterworth low pass IIR filter is an effective technique for such application where the flat response in the passband is needed in addition to noise reduction and signal conditioning. But still filtering is not always the best suitable technique because it leads to the loss of some important information during the signal processing.

After applying the filter, the total data is divided into a total of 100 window segments. The whole signal is executed instead of taking some specific portion of the signal which is reported in some previous studies. A fixed portion of data may be used to identify the fault location in the signal but it is hard to find the best and exact signal portion to distinguish the healthy and faulty parts. The main advantage of the segmented window process is the capability to examine the whole signal to find the best classification accuracy. Again, this technique can also be efficient for transient fault analysis.

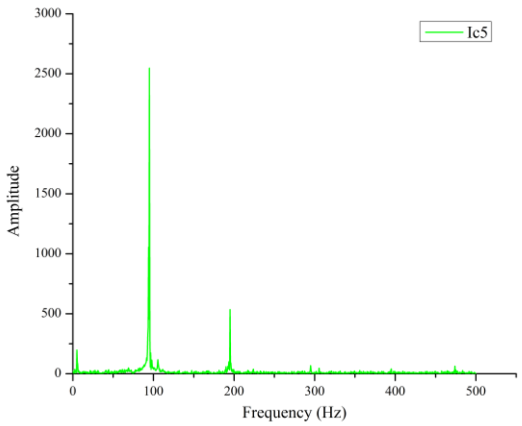
Fig.2 shows the three cases of healthy, 2% ITSC, and 5% ITSC filtered Fast Fourier Transform (FFT) of phase C of a specific segment where ITSC fault is implemented. This is investigated to observe the primary oversight between different cases of the data set. This graph is an indicator to inspect the visual difference between healthy and faulty conditions with respect to different frequency amplitudes. The FFT signal has differences but is not highly distinguishable to identify each case only with the frequency characteristics. The remaining two phases have observed a similar type of filtered FFT response but have not implemented ITSC in those phases.



(a)



(b)



(c)

Fig.2 Comparison of (a) healthy (b) 2% ITSC (c) 5% ITSC with FFT of filtered current signal in Phase C.

C. *Data segmentations:*

In the practical case solution data segmentation is a crucial step for the extraction of features from a larger data set. The process is done by dividing the whole signal into smaller and manageable pieces to extract meaningful patterns and information which helps detect the faults [15]. This may help to understand the data's nature and characteristics adequately. Segmenting the data allows machine learning algorithms to focus on different parts of the data, resulting in more precise and efficient analysis and prediction. Segmentation facilitates the comprehension of statistical features of individual segments, such as various models or patterns of distribution. In this study, the time-domain current signal of 200s is divided into 100 individual segments. As the sampling frequency is 10kHz, each window segment contains 20000 data points whereas an individual segment has the recorded time of 2s. The total signal is analyzed for the healthy and multiple faulty conditions. This eventually helps to find out the well-performing and robust features of the machine learning classification.

III. The Procedure of Fault Diagnosis Based on Machine Learning

This section has represented the necessary steps to understand the core procedures for the classification process. The previous section already describes the data preprocessing and the segmentation details. Now the main ingredient to perform the machine learning classification is done by feature extraction and feature selection using the WFS technique. This study provides an enhanced WFS approach that selects possible candidates primarily through unique feature combinations, with the ultimate objective of picking the fittest features subset with the smallest amount of computing resources.

The total features set are divided into 9 levels. Each level number represents the number of features used for the classification. Every set of features is grouped with the three-phase combination. TABLE I displays the statistical features details and the mathematical expression that is extracted from the dataset segments. The features crest factor (A), impulse factor (B), kurtosis factor (C), margin factor (D), mean factor (E), RMS factor (F), shape factor (G), skewness factor (H), and standard deviation factor (I) are extracted accordingly for all healthy and faulty conditions.

All features hold different patterns, characteristics, and information of the data set and the main inputs for the machine learning model training and testing purpose. Moreover, it is important to note that 70% data is used for training and 30% data is used for testing purposes for the primary evaluation of algorithm performance with WFS for all possible levels. Furthermore, the WFS technique of feature selection not only helps the model consistency but also minimizes the computational bias, overfitting, and evaluation time [16]. The higher dimensional features are more time-consuming for the calculation. After the first level, the combination is checked by combining the best performer of the previous level with the rest of the features.

Fig. 3 outlines the workflow for the performed work. After the completion of data preprocessing and segmentation, feature extraction is a crucial term for reducing the dimensionality and the computational burden for a longer set of data. Specifically, statistical features are extracted for the machine learning classification for this study. The classification is done between healthy and faulty conditions with statistical features. Each phase has 9 features with three-phase current signals a total number of 27 different features for all 100 window segments. Lastly, with the help of the features wrapped-based sequential forward selection, the optimal performing subset is investigated.

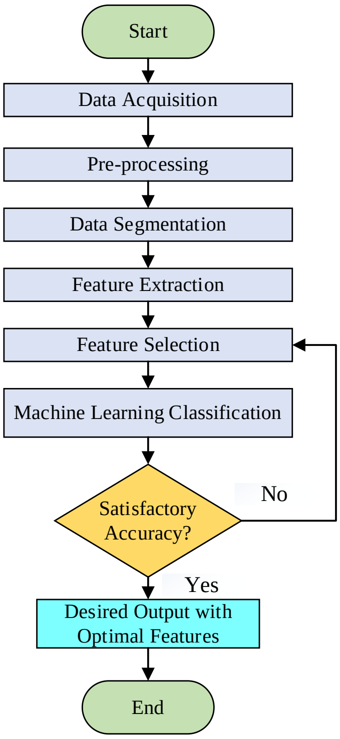


Fig.3 Flowchart of fault classification method.

In this study, four classification algorithms are chosen for the machine use of machine learning classification. A short description of the classifiers is highlighted below:

A. Decision Tree (DT):

Decision tree (DT) is a type of prediction algorithm that generates a tree-like structure of choices and results by continuously splitting a dataset into subsets according to relevant features. The algorithm chooses a feature that best divides the data into uniform subsets, with the root node initially representing the full dataset. Each subset goes through this procedure again, creating decision nodes that stand in for features. It checks until specific stopping conditions are satisfied, such as reaching a maximum tree depth or a minimum quantity of samples in a node. The last nodes contain the decisions or desired results.

B. Random Forest (RF):

Random forest (RF) trains multiple decision trees and the algorithm first selects subsets of the training data at random. After independent training, each tree casts a vote for the expected result. The outcomes of each tree are summed up during prediction, and the final categorization or mean prediction in regression is decided by a majority vote. Using an ensemble technique reduces overfitting while improving generalization and prediction accuracy.

C. Extreme Gradient Boosting (XGB):

XGB, shortly extreme gradient boosting, differs from RF by focusing on the optimization of a particular objective function throughout the training process. It achieves this by continuously adding trees to minimize the gradient of the loss function. The model uses regularization methods to manage the complexity of individual trees and applies cutting to eliminate branches that do not substantially enhance the model's performance.

D. Support Vector Machine (SVM):

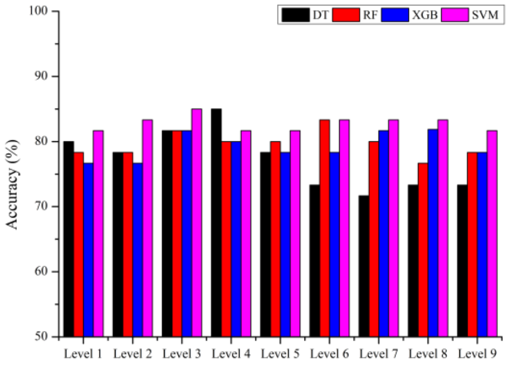
The primary objective of SVM is to choose the best-suited hyperplane that optimizes the separation between various categories in a dataset that has been labeled. The hyperplane is specifically located to maximize the distance between the closest data points of each class, which are known as support vectors. SVM employs a kernel technique to convert the input space, enabling the identification of a separating hyperplane even when the data is not linearly separable. The optimization procedure seeks to maximize the margin and decrease classification errors using a regularization parameter.

TABLE I. LIST OF EXTRACTED FEATURES

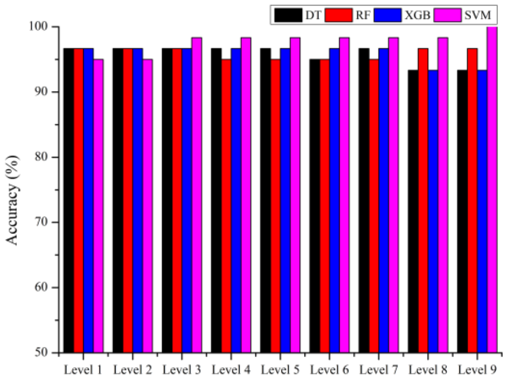
No.	Parameter	Equation
A	Crest Factor	$X_{CREST}=\dfrac{X_{max}}{\sqrt{(\frac{1}{N}\sum_{i=1}^{N}(x_i^2))}}$
B	Impulse Factor	$X_{IMP}=\dfrac{X_{max}}{\sqrt{(\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}}$
C	Kurtosis Factor	$X_{KURT}=\dfrac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^4}{(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2)^2}$
D	Margin Factor	$X_{MARGIN}=\dfrac{X_{max}}{(\sqrt{(\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert})^2}$
E	Mean Factor	$X_{MEAN}=\frac{1}{N}\sum_{i=1}^{N}x_i^2$
F	RMS Factor	$X_{RMS}=\sqrt{(\frac{1}{N}\sum_{i=1}^{N}(x_i^2)}$
G	Shape Factor	$X_{SHAPE}=\dfrac{X_{RMS}}{\sqrt{(\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}}$
H	Skewness Factor	$X_{SKEW}=\dfrac{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^3}{(\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2)^{\frac{3}{2}}}$
I	Standard Deviation Factor	$X_{STD}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}$

IV. CLASSIFICATION ACCURACY WITH DIFFERENT MACHINE LEARNING ALGORITHMS

Fig. 4 shows the accuracy comparison between the healthy to 2% & 5% ITSC faulty conditions. In Fig.4(a), it is evident that level 3 holds the best overall accuracy with respect to other feature combinations. For choosing a level, the number of selected features is the indicator of the level number. Among them, level 3 has combined with RMS factor (F), standard deviation factor (I), and crest factor(A) which is the optimal feature combination for both healthy to 2% ITSC and healthy to 5% ITSC fault detection. Nevertheless, the performance of all four machine learning algorithms is not the same for detecting all the individual levels for both condition fault detection. The key performance indicator is classification accuracy. The other two performance indicators receiver operating characteristics (ROC) area under the curve (AUC) and the F1 score are also shown in TABLE II.



(a)



(b)

Fig.4 Classification accuracy comparison between healthy & (a) 2% ITSC (b) 5% ITSC using wrapper-based feature (WFS) selection.

The accuracy's mathematical term is shown in (1). The classifier's overall performance potential thresholds are presented by the receiver operating characteristic (ROC) area under the curve (AUC). The ROC curve demonstrates the relationship between the true positive rate (TPR) and the false positive rate (FPR) of a classifier that has been trained. The TPR and FPR may be computed using the following formulas of (2), and (4) accordingly. The last F1 score's formula is represented in (5) which is stated in support of the precision and recall formula of (2), and (3).

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Recall}=TPR=\frac{TP}{TP+FN} \tag{2}$$

$$\text{Precision}=\frac{TP}{TP+FP} \tag{3}$$

$$FPR=\frac{FP}{FP+TN} \tag{4}$$

$$\text{F1 Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{5}$$

Where, TP, TN, FP & FN represent true positive, true negative, false positive, and false negative respectively.

TABLE II. WFS-BASED BEST FEATURES OF VARIOUS LEVEL

		WFS 0-2%			**WFS 0-5%**		
Level No.	Algorithm	Accuracy (%)	ROC AUC (%)	F1 Score (%)	Accuracy (%)	ROC AUC (%)	F1 Score (%)
Level 1	DT	80	80	80.64	96.67	96.67	96.67
	RF	78.33	87.94	80	96.67	98.50	96.55
	XGB	76.67	86.89	77.42	96.67	99.11	96.55
	SVM	81.67	90.67	83.07	95	99.77	94.91
Level 2	DT	78.33	78.33	76.36	96.67	96.67	96.67
	RF	78.33	87.44	77.19	96.67	98.77	96.55
	XGB	76.67	87.22	75.86	96.67	98.77	96.55
	SVM	83.33	90.77	82.14	95	99.77	94.91
Level 3	DT	81.67	81.67	81.35	96.67	96.67	96.55
	RF	81.67	88.61	80.70	96.67	99.77	96.55
	XGB	81.67	85.44	81.35	96.67	99.67	96.55
	SVM	85	91.44	83.63	98.33	99.89	98.30
Level 4	DT	85	85	86.15	96.67	96.67	96.55
	RF	80	88.27	77.78	95	99.61	94.73
	XGB	80	83.44	79.31	96.67	99.67	96.55
	SVM	81.67	87.78	80	98.33	99.88	98.30
Level 5	DT	78.33	78.33	77.19	96.67	96.67	96.55
	RF	80	87.33	77.78	95	99.77	94.73
	XGB	78.33	84.22	76.36	96.67	99.66	96.55
	SVM	81.67	88.11	80	98.33	98.33	98.30
Level 6	DT	73.33	73.33	74.19	95	95	94.91
	RF	83.33	88.11	82.14	95	99.67	94.73
	XGB	78.33	87	77.19	96.67	99.67	96.55
	SVM	83.33	86.77	82.14	98.33	99.77	98.30
Level 7	DT	71.67	71.67	73.01	96.67	96.67	96.55
	RF	80	89.16	78.57	95	99.22	94.73
	XGB	81.67	88.22	80.70	96.67	98	96.55
	SVM	83.33	87.66	82.14	98.33	99.88	98.30
Level 8	DT	73.33	73.33	75	93.33	93.33	93.10
	RF	76.67	87.5	75	95	99.55	94.73
	XGB	81.67	88.22	80.70	96.67	98.11	96.55
	SVM	83.33	87.77	82.14	98.33	99.88	98.30
Level 9	DT	73.33	73.33	73.33	93.33	93.33	93.10
	RF	78.33	88.83	76.36	96.67	100	96.55
	XGB	78.33	87.11	77.19	93.33	99	92.85
	SVM	81.67	87.33	80	100	100	100

TABLE II has listed all accuracy, ROC AUC, and F1 scores for all levels and algorithms. Each algorithm has used the default hyperparameter settings. For 0-2% ITSC, DT, RF, and XGB have shown the best accuracy of 81.67% individually and SVM with 85% respectively in level 3. The ROC AUC and F1 scores have been recorded highest using SVM with the values of 91.44% and 83.63% accordingly which is a good indicator of classification accuracy. DT algorithm has recorded 85% in level 4 but the other algorithms are not able to surpass the accuracy of the previous level 3.

As per Fig.4(b), 0-5% ITSC has a better performance with the same level 3 which is considered optimal for the classification. Apart from that, the 0-5% ITSC detection has the lowest accuracy obtained with 93.33% by DT in level 9. Level 9 also shows 100% classification accuracy in SVM due to its characteristics but the RF algorithm is performing the same performance as level 3 and the other two algorithms DT and XGB the better performers than level 9. Again, the computational time is another factor for choosing the lower dimensional level as an optimal feature subset because the higher dimensional data need more training and prediction time [17]. It is obvious that the 2% ITSC is not a better performer than the 5% ITSC fault detection from the healthy condition. This happened because the 2% ITSC properties are near to the healthy one. On the other hand, 5% of ITSC detection is well performed because of the clear distinguishable features available for the classification while making the visualization of features.

The best-performing feature combination at every level is listed in TABLE III for the two types of ITSC severity. All the possible combination is tested for all individual levels and the best performer is marked. Fig.5 has illustrated the 10-fold cross-validation mean result which indicates the robustness of the evaluated model. 0-2% ITSC has the lowest validation score with single features of level 1. The best features validation is obtained in level 3 by RF with the amount of 85% and the other algorithms are above 80%. 0-5% has the best mean validation score of 98.57% with SVM in the optimal level 3. Level 9 has the highest amount of mean cross-validation score but is not selected as optimal because of the larger computational complexity.

TABLE III. LEVEL-WISE BEST FEATURES FOR CLASSIFICATION

	Best Features	
Level No.	0-2% ITSC	0-5% ITSC
Level 1	F	I
Level 2	F,I	I,F
Level 3	F,I,A	I,F,A
Level 4	F,I,A,H	I,F,A,B
Level 5	F,I,A,H,B	I,F,A,B,D
Level 6	F,I,A,H,B,G	I,F,A,B,D,H
Level 7	F,I,A,H,B,G,C	I,F,A,B,D,H,G
Level 8	F,I,A,H,B,G,C,D	I,F,A,B,D,H,G,E
Level 9	F,I,A,H,B,G,C,D,E	I,F,A,B,D,H,G,E,C

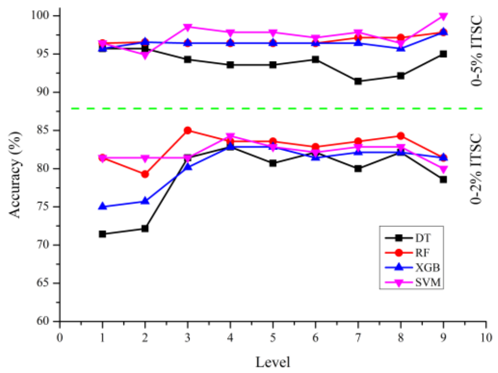


Fig.5 Mean accuracy results of 10-fold cross-validation.

V. CONCLUSION

This study has shown the capability for the classification of low severity ITSC fault detection by MCSA of PMSMs with the help of a data-driven model using machine learning. The recorded historical three-phase current data have been utilized by some preprocessing and feature extraction for the classifiers. A total of 9 separate levels have been compared with WFS to understand the effectiveness of current signal features for the diagnosis of ITSC fault in a lower severity. The results obtained by the classifier have shown that only a higher dimension of features does not guarantee the best performance at all times. Among the classification algorithms, SVM is better than the other algorithms in most of the case. Also, the WFS-based feature selection technique is not only a good way to ensure optimal performance but also an efficient mechanism for reducing computational complexity. The next level of this work can be based on the frequency domain features, deep learning features, texture features, and so on for more effective identification of fault severity at the lower levels.

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