2

Literature Survey

Induction motors are the one of the most extensively used AC motors owing to their advantageous features such as low cost, cheap maintenance, feasible size, and ruggedness. They are often termed as the workhorse of the industry as they find applications in many sectors. Evidently, they offer high reliability under the extreme stresses of an industrial environment. However, these stresses which can be electrical, thermal, mechanical or environmental, can induce incipient faults in the motor. These incipient faults tend to grow stern which can damage the motor to its complete shut-down. Generally, the manufacturers rely on simple protection schemes, including over-current and over-voltage protection to prevent any damage. However, with the growing complexity of the complete plant where these motors are installed, the tasks handled become more complex. Thus, relying on such schemes only would not help to escape the consequences of incipient faults.

In this scenario, condition monitoring of the motor plays an important role in detecting/identifying the faults in embryonic stages. It aids the machine engineers to prepare in advance for its maintenance or repair. It has been stated in [Rai and Upadhyay, 2016] that condition-based maintenance coalesces three entities together: 1. Condition monitoring, 2. Fault diagnosis and 3. Fault Prognosis as depicted in Figure 2.1. Condition monitoring tools include vibration, acoustic, motor current signature analysis (MCSA), induced voltage, temperature etc. which helps in collecting the raw data of the system. The Fault diagnosis processes the data and gives decision based on the analysis. Lastly, the fault prognosis predicts the healthy life of the machine with the existence of the faults detected in fault diagnosis process.

Hitherto, various techniques for electrical and mechanical fault diagnosis in the induction motors are reported in the literature [Liu and Bazzi, 2017; Wang et al., 2016; Rai and Upadhyay, 2016; Gandhi et al., 2010; Grubic et al., 2008]. These techniques are broadly based on vibration monitoring, motor current analysis, temperature measurement, acoustic noise measurement, partial discharge measurement, axial flux measurement [Mehrjou et al., 2011]. The current based analysis has been adopted widely as the stator currents are affected by electrical (stator and rotor faults) and mechanical faults (bearing fault) due to electromechanical energy conversion. Also, the easy availability of the current sensors makes it a cost-effective alternative to other invasive

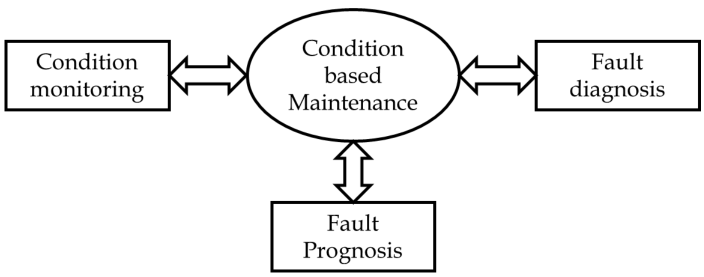

Figure 2.1 : A schematic of a condition based maintenance system (adapted from [Rai and Upadhyay, 2016])

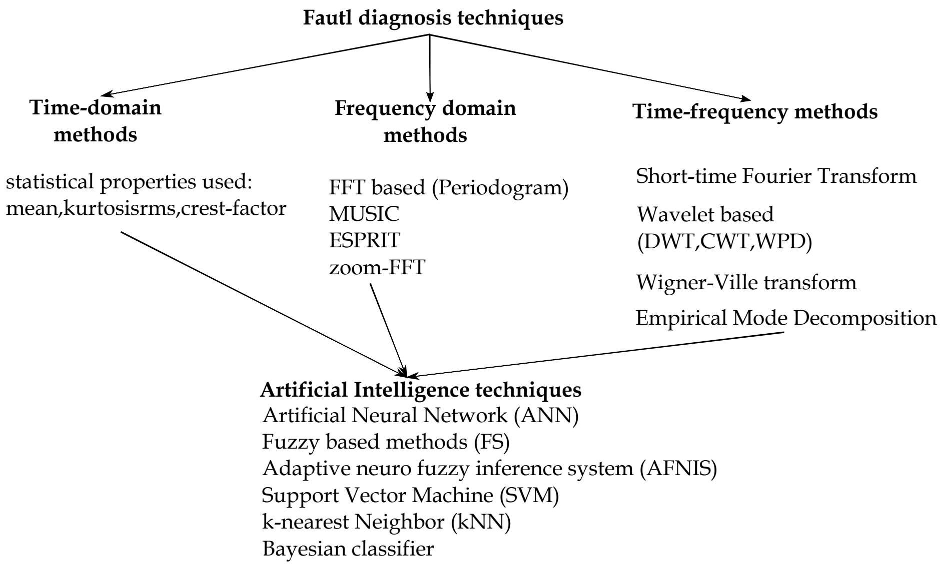

Figure 2.2 : Techniques used for fault diagnosis of an induction motor

techniques. Another advantage is that it can be remotely controlled while other methods require sensors which are costly and are placed inside the motor. The current signals can be recorded at the start-up or steady-state conditions. Thus, the current based fault diagnosis solutions are simple and cost-effective.

The stator current ideally consists of one frequency component at the supply. In the presence of incipient faults, there are unbalances in the motor windings or modulations in the air-gap eccentricity, which causes significant modulations in the air-gap harmonic distribution. These changes create specific harmonics in the stator current spectrum related to incipient faults. Thus, the stator current spectrum can be seen as a rich source of fault signatures. Also, as reported in [Stincescu et al., 1999], the space and time harmonics are shown to be influencing the harmonics of stator currents. Thus, the harmonic content can be very useful for detecting faults inducing such harmonics. These preliminary changes can be observed with the help of motor current signature analysis (MCSA) which performs spectral analysis to identify frequencies related to the incipient faults in an induction motor. This is the classical approach for fault detection which is still being used in combination with other signal processing tools for the fault diagnosis strategies.

This chapter includes the literature survey of the fault diagnosis techniques and algorithms for various incipient faults in a three-phase induction motor. It is divided into three categories pertaining to three fault types considered in the study viz., bearing, stator, rotor faults.. For every fault category, the fault diagnosis techniques (FDTs) proposed in the literature have been divided into three domains:

1. Time-domain based FDTs, where signals are processed and analysed in the time-domain
2. Frequency-domain based FDTs, where the time-domain signal is transformed into frequency-domain through conventional and high-frequency resolution analysis methods
3. Time-frequency domain based FDTs, where both time and frequency are preserved, and
4. Machine learning (ML) based FDTs which includes the use of several ML tools such as an artificial neural network (ANN), support vector machine (SVM), k-means algorithm, k-nearest neighbour (kNN), fuzzy logic, genetic algorithms (GA) etc., with the data obtained from above three category based techniques. In general, various methods used for the fault diagnosis are summarized in Figure 2.2. A basic flowchart of the fault diagnosis algorithms is shown in Figure 2.3.

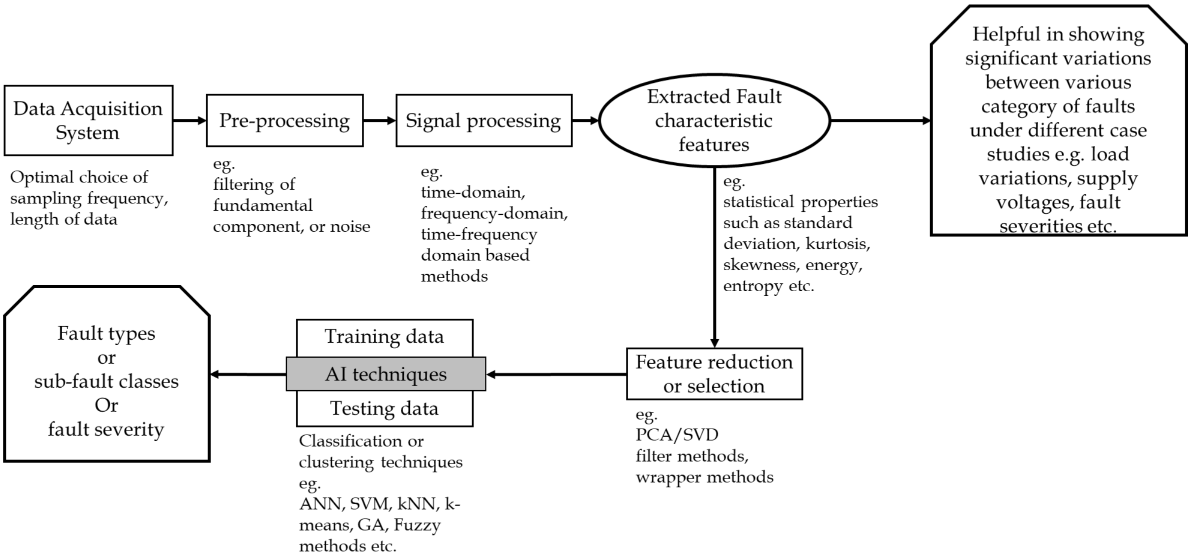

Figure 2.3 : Basic flowchart of the fault diagnosis techniques

2.1 BEARING FAULTS

Bearing faults are the major contributor of faults with 40% [Group et al., 1987] share in total motor faults. The considered faults in the bearing include outer-race, inner-race, broken cage and eroded balls faults. Bearing fault diagnosis has been studied using vibration and current data analysis. A number of techniques are developed and proposed for bearing failure analysis in the three-phase induction motors [Liu and Bazzi, 2017; Rai and Upadhyay, 2016; Filippetti et al., 2013; Zhang et al., 2011].

Vibration analysis is a commonly used approach for bearing fault detection which has been reviewed in [Kumar et al., 2015; Liu and Bazzi, 2017]. The requirement of additional vibration modules/ transducers, necessary digital processing and their precise placement makes it a costly and difficult solution [Singh and Kazzaz, 2004]. On the contrary, the motor current signature analysis (MCSA) is a cost-effective and non-invasive alternative that requires only current measurement using rather cheap current sensors. Generally, these sensors are already installed for measuring electrical quantities with the motor. The focus is on the current based analysis along with the other electrical quantities for fault diagnosis of bearing faults.

2.1.1 Time-domain based FDTs

In the case of bearing faults, the significant portion of techniques is either frequency domain or time-frequency domain. There are some articles which have utilized features in time-domain such as in [Siegel et al., 2011] root mean square analysis, high-order statistical approaches [Prieto et al., 2012], squared envelope analysis [Antoni, 2007], spectral kurtosis analysis [Leite et al., 2015; Wang et al., 2016] have been used. These techniques involve the use of features extracted from the raw signals; where these features are in the time-domain.

2.1.2 Frequency based FDTs

The relation between defect frequencies in the current spectrum and vibration spectrum is established by Schoen et al in [Schoen et al., 1995a]. In the MCSA, Fourier transform of the current signals is determined which helps in showing fault specific peaks in the spectrum [Schoen et al., 1995b; Benbouzid, 2000; Lindh et al., 2003; Onel et al., 2005]. MCSA aims to analyse current harmonics related to rotating flux components induced by the incipient faults. In recent studies [Pandarakone et al., 2019, 2017; Palácios et al., 2016], the features extracted from spectral characteristics are utilized to detect faults with the multi-agent systems. The spectral analysis of different types of the bearing faults are performed keeping the efficiency of the motor in check [Frosini and Bassi, 2010]. In [Yang et al., 2016], the authors proposed a scheme based on Independent Component Analysis (ICA) and Fast Fourier Transform (FFT) of the current signals. The features of FFT of the current signal and Hilbert Huang Transform of vibration signals have been used together to perform bearing fault classification using a hierarchical classifier [Esfahani et al., 2014]. The authors in [Mbo'o and Hameyer, 2016] reported the detection of two-width level outer-race defect using Welch power spectral density of stator current and linear discriminant analysis. The limitations of these proposed techniques are that they are neither implemented for many defects in bearing simultaneously nor precise enough for the proposed frequency components in the analysis. The advantage of frequency-domain analysis lies in its high gain information on fault sensitive frequencies and low sensitivity towards noise. However, it is limited to only stationary signals. FFT is a widely used frequency domain tool for spectral analysis; but, it provides frequency information without time localisation, which in turn may not be useful in fault diagnosis.

In order to overcome the limitations of low-frequency resolution provided by FFT, there are high-frequency resolution analysis techniques proposed such as multiple-signal classification (MUSIC) [Elbouchikhi et al., 2016; Garcia-Perez et al., 2011], and estimation of signal parameter via rotational invariance technique (ESPRIT) [Trachi et al., 2016b]. Total least squares-ESPRIT and generalised likelihood ratio test are used to determine the presence of fault [Trachi et al., 2016b]. Reference [El Bouchikhi et al., 2015] proposed a parametric spectral estimator based on maximum likelihood estimator for high-resolution analysis of current signals. These methods solve for a high amount of data required for high resolutions under spectral analysis performed using FFT. However, they are computationally expensive and time-consuming [Liu and Bazzi, 2017]. Although in [Boudinar et al., 2016], the authors have tried to reduce the computational time for stationary load and constant motor speed. The performance of these methods deteriorates if the noise levels increase.

2.1.3 Time-frequency based FDTs

The shortcomings of spectral based analysis under non-stationary environment are dealt by various advanced signal processing techniques with the multi-resolution capability in time-frequency domain [Rai and Upadhyay, 2016; Feng et al., 2013; Zhang et al., 2011; Singh and Ahmed Saleh Al Kazzaz, 2003]. These techniques aim to provide frequency information with localised time which is a helpful feature in analysing non-stationary signals. Such methods are also helpful in transient signal analysis, frequency selective spectral analysis. These methods include linear methods such as short-time Fourier transform (STFT) and wavelet transform (WT); non-linear methods such as Wigner-Ville Distribution (WVD), and non-parametric methods such as Empirical Mode Decomposition (EMD) [Lopez-Ramirez et al., 2016; Climente-Alarcon et al., 2014; Lei et al., 2013]. EMD helps in decomposing the signal into intrinsic mode functions (IMF) to reveal more information. In [Elbouchikhi et al., 2017], the variance of the instantaneous amplitude and frequency along with the energy of the IMFs calculated from EMD is used as fault severity indicators. The EMD of motor voltage is proposed [Dalvand et al., 2016], where the global kurtosis of instantaneous frequency is used as the fault indicator. This study has only been validated for outer-race way defect. The fault indicators above-mentioned are susceptible to changes in fault conditions.

The use of STFT has been reported in [Lopez-Ramirez et al., 2016], where energy of spectrogram for healthy and faulty bearing conditions are observed. Fault detection based on stator current spectral subtraction using STFT is proposed [Bouchikhi et al., 2013]. STFT and

WVD are window-based transforms which suffer from fixed window size limitation and existence of cross-terms respectively. These limitations are overcome by Wavelet Transform (WT) where the window size is dependent on frequency; a wider window is used for low frequencies and vice-versa also exists.

The multi-resolution capability of WT and its extensions such as wavelet packet decomposition (WPD) have been exploited in the analysis of stator current signals for detecting bearing faults in the recent past [Liu and Bazzi, 2017; Yan et al., 2014; Peng and Chu, 2004]. WT provides information in both time and frequency domain with a fair resolution. The window referred as mother wave has size, wider for low frequency and narrower for high frequencies. The breakdown of the current signal into coefficients representing different frequency bands has been proved to be an efficient source of fault detection. Eren et al. [Eren and Devaney, 2004] analysed the specific frequency bands of defects in the bearing using Wavelet Packet Decomposition (WPD). Narrow bandwidth filter banks implemented with the aid of Wavelet analysis is reported in [Chow and Hai, 2004] for multiple fault diagnosis including bearing faults. Another scheme based on the stator current decomposition using WPD employing Meyer mother wavelet is proposed in [Zarei and Poshtan, 2007]. In [Lau and Ngan, 2010], the authors have used wavelet packet transform (WPT) up to a range of defect frequencies to decompose current signals which are further analysed using FFT to show the fault existence and severity. The energies associated with wavelet decomposition of stator current signals have been used to detect bearing faults in [Kapoor et al., 2014]. In [Zarei and Yousefizadeh, 2014], Park's vector is used to eliminate the main frequency and amplify the faulty components of stator current signals which are further analysed by WPD to detect faults. In [Singh and Kumar, 2017], the Continuous Wavelet Transform (CWT) is used for the detection of outer-race detection. Although, it takes high computational time due to calculation of scales of wavelet coefficients. The frequency spectral subtraction using various extensions of WT such as discrete (DWT), stationary (SWT) and WPD has been proposed in [Deekshit Kompella et al., 2017] for bearing fault detection.

2.1.4 Machine learning based FDTs

Machine learning methods are widely used to construct fault diagnostic systems. The ability to model non-linear complex system and mapping of this non-linear data into feature space has attracted much attention in the scientific community [Liu et al., 2018; Widodo and Yang, 2007]. These ML tools include fuzzy based methods, artificial neural network (ANN), neuro-fuzzy systems, support vector machine (SVM), decision tree (DT), k-nearest neighbour (k-NN), Bayesian classifier. These techniques are based on an idea to train a machine (a computer) to understand real-world patterns/problems such that it can learn and adapt like humans. They provide capability to computers to learn rather than being explicitly programmed. For fault diagnosis, several contributions have been reported based on the combination of signal processing tools (described above) and ML techniques. There is immense utilisation of ML techniques in synchronism to the signal processing techniques that helps the researchers to develop robust and reliable algorithms for the fault diagnosis.

Earlier applications of the neural networks for bearing fault diagnosis are reported in [Li et al., 2000; Kowalski and Orlowska-Kowalska, 2003]. The RMS values of components (defect frequency selective) extracted from WPD of the current signals are used for the detection of outer-race and cage faults in [Eren and Devaney, 2004]. A robust classifier based on artificial ant system is proposed for fault detection of bearing and BRB faults using features extracted from the Park's vector components of current and voltages. In [Schmitt et al., 2015], the authors have proposed a bearing fault detection scheme based on information-theoretic measures (relative entropy, Bhattacharyya distance and Lempel-Ziv complexity measure) based on Wavelet Packet Decomposition (WPD) of current signals, which are fed to Artificial Neural Network (ANN) to classify inner and outer-race faults. A scheme based on adaptive neuro-fuzzy inferencing system (AFNIS) which utilizes five machine parameters is proposed for bearing fault detection [Ballal et al., 2007]. The efficacy of AFNIS for bearing fault diagnosis is also presented in [Ertunc et al., 2013]. In [Widodo et al., 2009], post-decomposition of start-up current signals using DWT, the features extracted are passed through ICA and PCA for dimensionality reduction and later they are fed to SVM for multi-class classification. The study by [Abid et al., 2018] used optimized SWT for feature extraction and artificial immune network nested within SVM for fault classification. With the use of DWT and matching pursuit based on current and vibration signals, the authors in [Ali et al., 2019] have compared 17 different classifiers for machine fault classification. Detection of minor bearing faults such as scratches are performed using FFT and ML tools in [Pandarakone et al., 2019]. Table 2.1 shows some more references used various techniques detecting different types of bearing faults.

Table 2.1 : FDTs for bearing fault diagnosis

Technique used	Feature Extraction	Feature Reduction/ Selection	Citations	Type of fault addressed
FFT	Spectral characteristics	-	[Pandarakone et al., 2018, 2017; Yang et al., 2016]	BF with scratches on OR
High-frequency resolution analysis	-	-	[Aimer et al., 2018; El Bouchikhi et al., 2015; Bouchikhi et al., 2013; Garcia-Perez et al., 2011]	OR, Cage and Ball fault
Park's transform	-	-	[Önel and Benbouzid, 2008]	IR, OR, ball
Fuzzy based	-	-	[Hassan et al., 2018]	OR, BRB, TF
Fuzzy-ARTMAP	Fourier-Bessel expansion	Generalized Discriminant Analysis	[Tran et al., 2013]	BF, BRB, EF,UB
ANN	Time-domain features	None	[Pandarakone et al., 2019; Zarei, 2012]	IR, OR
QDA-SVM	Vibration, acoustic, PSD of current	Linear Discriminant Analysis	[Esfahani et al., 2014]	IR, OR, EF
k-means clustering	current	-	[Chaudhury and Gupta, 2006]	BF, EF
Wavelet denoising	vibration, current	SVM	[Abbasion et al., 2007]	OR, IR, Ball

2.2 STATOR WINDING FAULTS

The faults in the stator are reported to be around 30%-40% of the total induction motor faults. Generally, these faults arise due to the insulation failure. The stator winding is subjected to various thermal or electrical stresses, mechanical vibrations, which deteriorates the winding insulation in the form of inter-turn shorting [Bonnett and Soukup, 1992]. Short circuit current causes localised heating of the winding which elongates the shorting into wider section. This results into phase to phase or phase to ground faults. Thus, the inter-turn shorts are the root cause of stator winding faults. Therefore, the detection of incipient stator winding inter-turn shorts (SWITS) is necessary in order to avoid severe damage to the windings. Several techniques have been reported for winding fault detection which includes the condition monitoring tools such as vibration, angular speed, current, induced voltage, acoustic signals, magnetic flux, temperature, torque, power, partial discharge, gas analysis, surge testing [Siddique et al., 2005]. Under the usage of current signals, various methods for fault diagnosis of stator windings are reported which includes analysis of negative sequence components, spectral analysis, high-resolution spectral analysis, Park/Concordia methods, high-frequency signal injection method, time-frequency analysis etc [Grubic et al., 2008]. These techniques are broadly divided in three categories, mentioned in Section 2.1. Thus, the state of the art of the fault detection for stator faults are categorised based on the technique used and are presented in the following paragraphs:

2.2.1 Time-domain FDTs

Several studies have been performed and reported for stator winding faults, which are based on either mathematical models or derived directly from the data. Among those, several diagnostic approaches based on sequence components of the motor's current, impedance and voltage have been reported for stator winding fault analysis in the literature. Due to inter-turn shorts, the machine impedance is changed which causes the unbalance in the currents drawn by the motor. This allows the flow of negative sequence currents which is a prominent parameter in detecting stator faults and is also reviewed in [Kliman et al., 1996; Arkan et al., 2001; Kohler et al., 2002; Tallam et al., 2003]. Off-diagonal elements of machine's negative sequence impedance matrix have also been analysed for turn-fault detection to mitigate the effects of supply unbalance [Lee et al., 2003]. Multiple reference frame theory in [Cruz et al., 2005] and information theory have also been utilized for the diagnosis based on negative sequence currents. Negative sequence currents generated from high-frequency voltage excitation to the induction motor have been analyzed in [Briz et al., 2009] for SWITS detection. Another sequence impedance-based SWITS has been proposed in [Cheng et al., 2010] in the presence of a multiple-motor system. An approach based on negative sequence currents and voltages for inter-turn fault impedance is presented in [Nguyen et al., 2017] compensating the effects of voltage unbalance, inherent asymmetry to detect the early fault, identify the faulty phase, and provide an estimate of the fault severity level. These current signals are also evaluated using the injection of high-frequency carrier signal in the induction motors [Briz et al., 2003]. Zero-crossing time of the stator currents has also been analysed for SWITS detection [Ukil et al., 2011]. The limitation of sequence components is that negative sequence currents are also developed because of supply unbalance, and are affected by load, torque variations, which limits its use for stator fault diagnosis.

Another time-domain approach for winding fault detection is performed using Park's transform. The authors in [Cardoso et al., 1999] proposed the analysis of three-phase stator current signals using the classical time-domain method i.e. Park's vector which for healthy motors take a circular shape while changes to elliptical shape for inter-turn shorts in the winding. The Extended Park Vector (EPVA) approach reported in [Cruz and Cardoso, 2001] also shows signatures of inter-turn faults. Concordia patterns for healthy, voltage unbalance and stator open phase under no-load and loaded conditions (elliptical patterns) are used to build a fault diagnostic scheme using fuzzy logic [Zidani et al., 2003; Diallo et al., 2005]. In [Das et al., 2014], the features of

Park vector modulus using EPVA in time, frequency, and time-frequency domain are extracted and non-linear based on detrended fluctuation analysis is performed whose features are fed to support vector regression with recursive feature elimination for classification of inter-turn faults under voltage imbalance and load variations. A combination of spectral analysis and Park's vector is reported in [Acosta et al., 2006] to develop an online monitoring system to diagnose inter-turn faults. Forward and backward currents with the help of Clarke transformation are computed and analysed for turn faults [Dorrell and Makhoba, 2017].

In [Eftekhari et al., 2013], the current signals are transformed on a 3D plane and the shape of the ellipse is used to detect turn faults and the phase-ground fault with their location and severity. The modal current and voltage signals are calculated from three-phase currents and voltages, then auto-correlation of their envelopes are found out. In [Ghanbari, 2016], the variance of the autocorrelation of modal current envelope is reported to be significantly different for healthy and 5% turn faults. A model-based study presented in [De Angelo et al., 2009], a vector-based on residual of the state observer is obtained from current estimation error for stator inter-turn short-circuit detection. The optimization-based FDTs are proposed in [Duan and Živanovic, 2015] where the fault parameters are estimated using least-squares estimation and optimised using sparse grid optimisation based on hyperbolic cross points for monitoring and detecting SWITS faults.

2.2.2 Frequency-domain FDTs

Machine faults induce characteristic frequencies in the current spectra due to periodical modifications in the machine vibrations and air-gap flux. Thus, the classical approach for fault detection is the spectral analysis which is conveniently explored using Fast Fourier Transform (FFT). In the case of stator winding faults, the FFT of axial leakage flux measured through sensors had been introduced in [Henao et al., 2003; Penman et al., 1994]. In the axial flux components, the frequencies detected are: $f_s = (k \pm n(1-s)/p)f$, where s is the slip, f is the supply frequency, p is the number of pole pairs, $k = 1, 3, ..,$ and $n = 1, 2, 3...(2p-1)$. These sensors are costly and sometimes inappropriate to the adverse environment. Manifestly, it started current based spectral analysis for stator winding faults.

The changes in the current and voltage spectra are also observed and analysed using FFT under stator faults [Benbouzid et al., 1999; Joksimovic and Penman, 2000; Thomson and Morrison, 2002]. It was shown in [Joksimovic and Penman, 2000] that the negative sequence current interacts with fundamental to produce speed ripple and in turn a change at three times in the fundamental component i.e. the variation in the third-harmonic as a result of stator faults. However, third harmonics are present due to other machine's residual asymmetries and the variation is not so sensitive for small faults [Cruz and Cardoso, 2004]. Third-harmonics and other triplen harmonics are analysed in [Nandi, 2006]. Some other rotor slot frequencies have been analysed for the SWITS which are observed under healthy, faulty and voltage unbalance conditions. It was shown that one frequency is prominent under faulty case only and does not deter with unbalance of voltages [Sharifi and Ebrahimi, 2011]. Frequency-domain methods are popular in the field of fault diagnosis; however, the limitations such as spectral leakage, low-frequency resolution and requirement of a long interval of measurement limit the use of spectral analysis of non-stationary signals. High-resolution spectral analysis based techniques such as MUSIC and ROOT-MUSIC are also used which are eigenvalue based frequency estimators[Benbouzid, 2000]. In [Li et al., 2015], a spectrum sync technique has been proposed for bearing and BRB fault detection where defect frequency bands are identified, synchronised and accentuated to highlight fault features. The high-frequency properties of the transient current signals obtained after voltage excitation through switching of the inverter have been reported in [Nussbaumer et al., 2014] to be useful for SWITS detection.

2.2.3 Time-frequency based FDTs

Over the years, the application of discrete wavelet transform (DWT) has been widely observed in rotor fault diagnosis of induction motors. In [Ponci et al., 2007], correlation of specific DWT detail coefficients are found for healthy and faulty conditions. In [Cusido et al., 2008], STFT and power spectral decomposition of detail coefficients of the decomposed current signals are formed for shorted turns and broken bar. The analysis of short circuit faults has been proposed using the decomposition of Park's vector magnitude signal using DWT in [Barendse et al., 2009] under speed transients for inverter-fed induction motor. Application of DWT and stationary WT is used to de-noise and reconstruct the current signals, then further decompose the reconstructed into detail coefficients [Devi et al., 2016]. The use of dual-tree complex wavelet transform (DTCWT) to decompose and then reconstruct the current signals for each of 13 levels is reported in [Seshadrinath et al., 2012]. Energy computed for each reconstructed waveform and fed to SVM to classify. In [Seshadrinath et al., 2014a,b], the energy of reconstructed current signals using DTCWT are fed to probabilistic NN and SVM for classification of healthy and inter-turn shorts under voltage unbalance and balance conditions. Similar work has been reported using vibration signals also in[Seshadrinath et al., 2013].

2.2.4 Machine learning based FDTs

The use of ML techniques for fault diagnosis has been reported in various articles and reviews for stator fault detection [Siddique et al., 2003; Dongyang and Shishuai, 2016; Liu et al., 2018]. These methods are popular as they are easy to implement, do not require system configuration and mathematical model for fault diagnosis. They are simply designed using the data acquired from the experimental tests of the induction motors. In [Nejjari and Benbouzid, 2000], inter-turn fault detection has been reported using Park's/Concordia vectors along with the aid of ANN for classification in case of voltage unbalance, open phase or turn shorts. In [Kowalski and Orlowska-Kowalska, 2003], the use of ANN and Kohonen Self-organizing Map (SOM) using statistical features of current signals under SWITS has been reported. In [Ghate and Dudul, 2010b], the authors have used ANN and SOM along with the use of PCA to indicate the efficacy of feature reduction. The use of an adaptive neural fuzzy system is proposed with the machine parameters such as temperature, current, speed etc. in [Ballal et al., 2007]. A feed-forward NN and LabVIEW based fault monitoring scheme using current and voltage data has also been proposed [Kolla and Altman, 2007]. In [Martins et al., 2007], the technique using principal components from Hebbian Based PCA based on alpha-beta currents from Clarke-Concordia transform is proposed, where they are fed to an unsupervised neural network for locating the fault. The use of feed-forward ANN trained using back-propagation is seen in [Bouzid et al., 2008], which is fed with phase difference between stator current and voltage signals for each phase for SWITS. Reference [Jover Rodriguez and Arkkio, 2008] has proposed detection of open phase and turn faults using fuzzy logic based on magnitudes of stator currents generated from the finite element method. A technique based time-series obtained using SOM based fuzzy clustering is proposed [D'Angelo et al., 2011], which is further analysed for change point detection using Metropolis-Hastings algorithm.

Fuzzy Min-Max (FMM) and Classification and Regression Tree (CART) has been used with harmonic components as input for fault diagnosis and classification of broken rotor bar, stator winding and bearing faults [Seera et al., 2013]. A wavelet-ANN based stator fault detection has been proposed in [Devi et al., 2010] with bi-orthogonal mother wavelet decomposed current signals. In [Devi et al., 2016], the same authors extended the work with the use of three-level modular neural network to classify various levels of SWITS in the three-phase induction motor. The features from the matching pursuit and discrete wavelet transform of current and vibration signals are fed to 17 classifiers to compare their performances in [Ali et al., 2019]. Using the application of SOM, the features selected from Relief, minimum redundancy and maximum relevancy based on the features extracted from Park's vector, zero-crossing instants of current signals are used for clustering stator winding faults [Haroun et al., 2018]. In[Bazan et al., 2017, 2019], the mutual information of three phase stator currents are fed to decision tree and ANN for classification of inter-turn shorts.

There are applications pertaining to the use of Hidden Markov Model (HMM) for the fault diagnosis such as in [Nakamura et al., 2010] impulse voltage is applied to winding terminals of the motor and the significant pattern obtained in the current are trained and tested using HMM for winding fault detection. The authors also used time-series signals generated using the envelope of three-phase stator current signals whose Gaussian Markov Model is constructed using reconstructed phase space, later which is later classified into classes such as broken bar and inter-turn faults using Bayesian Maximum likelihood classifier [da Silva et al., 2008]. In [Verma et al., 2014], mulit-scale entropy is calculated for wavelet denoised current and vibration signals, whose grey relational coefficient are used with fuzzy logic for fault diagnosis. Fuzzy Min-Max (FMM) and Classification and Regression Tree (CART) has been used with harmonic components as input for fault diagnosis and classification of broken rotor bar, stator winding and bearing faults [Seera et al., 2013]. A combination of Park's transform and cross-wavelet transform is proposed in [Das et al., 2011] to extract features and then use Rough set theory for classification for severity detection in SITS cases. Matching pursuit and DWT are used to extract features from current and vibration signals which are fed to 17 classifiers to detect and classify faults [Ali et al., 2019]. Thus, it can be observed that artificial intelligence techniques find tremendous and successful applications in the field of condition monitoring and can be used either stand-alone or in combination with other signal processing tools to make a robust fault diagnosis algorithm. Some more articles based on different techniques are presented in Table 2.2.

Table 2.2 : FDTs for stator fault diagnosis

Technique used	**References**	**Fault considered**	**Classification Accuracy**
Negative and Positive Sequence current	[Wang et al., 2016; Yun et al., 2009; Wu and Nandi, 2008]	SWITS, faulty phase detect; Single turn fault	-
Fuzzy logic based and Neural network approach	[Godoy et al., 2015]	SWITS, rotor eccentricity; SWITS	94
Time-frequency analysis (DWT)	[Seshadrinath et al., 2012]	SWITS with and without voltage unbalance	96.62
Cross-WT and Park's transform	[Das et al., 2011]	SWITS	90%
RBF-MLP Neural Network	[Ghate and Dudul, 2010a]	Eccentricity and SWITS	98.41
SVM-Regression	[Das et al., 2014]	SWITS	80.8 - 90%
FMM-CART	[Singh et al., 2013]	SWITS, Eccentricity, BF	98.25%

2.3 BROKEN ROTOR BAR FAULTS

Faults in any rotor produce asymmetrical rotor currents, which changes many other machine parameters. For reliable detection and estimation of broken bars in an induction motor, there are several parameters which can be monitored and worked upon such as stator current, air-gap torque, induced voltage, power, angular speed, electromagnetic field, acoustic and vibration signals [Mehrjou et al., 2011]. It has been widely established that broken bars produce frequency components in the current spectrum at $(1 \pm 2s)f$, where $'s'$ is the slip frequency and $'f'$ is the supply frequency. These components are known as side-band components for fundamental frequency $'f'$. At $2ksf$ frequency component, the other low-frequency torque and speed harmonics emerge. The fault diagnostic techniques (FDTs) have been divided into four sub-sections based on the domain they broadly belong to. The fourth sub-section has been dedicated to Machine learning based BRB fault-FDTs, where the use signal processing techniques along with the use of ML-based methods are presented.

2.3.1 Time-domain based FDTs

Some time-domain techniques have been employed such as in [Puche-Panadero et al., 2009] for amplitude demodulation to detect rotor faults. This demodulation has been performed in [Bellini, 2009] quantitative evaluation of faults. In [Ukil, 2012], the use of envelope analysis of the stator current is reported for the rotor fault detection. A simplified time-domain analysis is proposed in [Riera-Guasp et al., 2012] using Gabor analysis of stator currents. Reference [Cruz and Cardoso, 2001] introduced BRB fault diagnosis using Park's vector approach, where the characteristic LSB components are shown to be detectable. In Park's vector approach to fault diagnosis of an induction motor, it converts the three-phase current signals into the two-phase system. It obtains a current pattern using these two signals, which results in a circular pattern for a healthy machine while it changes to an ellipse for a faulty condition. The major axis of the ellipse is found in relation to the severity of the fault. However, reference [Zhang et al., 2007] has shown that these components are not detectable under low-loads. A combination of Spectral analysis and Park's vector is reported in [Acosta et al., 2006] to develop an online monitoring system to diagnose BRB and inter-turn faults. The authors in [Gyftakis et al., 2017] have proposed the use of filtered PVA and EPVA to make rotor slot independent for efficient BRB fault detection. In a model-based study presented in [Bachir et al., 2006], a new induction motor model is proposed with stator inter-turn and BRB faults and fault diagnosis has been proposed using Park's rotor resistance.

2.3.2 Frequency-domain based FDTs

The classical spectral methods of broken rotor bar fault detection revolves around the side-band frequencies computed using Fourier transform via FFT [de Jesus Romero-Troncoso, 2017; Filippetti et al., 2013; Mehrjou et al., 2011; Yazici and Kliman, 1999]. The harmonics present were used as an indicator of BRB faults [Kliman et al., 1988]. The relation between the side-band amplitudes and the number of broken bars were also investigated in [Siau et al., 2004]. However, reference [Didier et al., 2007] showed that this fault indicator is dependent on load inertia and load torque. Reference [Bellini et al., 2002] has shown that these magnetic asymmetries also give arise to frequency components in the spectral analysis. The phase of the current spectrum has been analysed for broken rotor bar fault signatures by [Bellini et al., 2008], inter-bar currents and magnetic asymmetry influence the side-band components diagnosis accuracy. The summation of two side-bands was found to be useful to detect number of broken bars as reported in [Filippetti et al., 1998]. In [Eltabach et al., 2007], the amplitude and the angular displacement of characteristic frequencies are shown to be useful; along with it the spectral analysis of instantaneous partial powers and current space vector modulus was also used. The authors extended this procedure [Eltabach et al., 2009] with Beirut diagnostic method for two-phase currents which is found to be independent of power factor angle and sum of two side-bands. Reference [Ayhan et al., 2005], power spectral density computed based on Welch's periodogram method is used as a fault parameter; the side-band information thus extracted is analysed with multiple-discriminant analysis (MDA). In another application of FFT on zero-crossing signals, spectral peaks at $2sf$ are found as fault indicator which is independent of motor's inertia, load variation and supply harmonics [Calis and Cakir, 2007, 2008]. High-order spectral analysis involving the use of power spectrum and bi-spectrum are used for the analysis of BRB faults in [Saidi et al., 2013]. In [Pires et al., 2013], the spectral analysis of the square of the stator current is analysed for BRB fault detection. The correlation between the current and vibration spectra is utilised for fault detection and has been implemented on FPGA to prepare an on-chip solution [de Jesus Rangel-Magdaleno et al., 2009]. Spectral analysis is an important tool to detect fault frequencies, but under low-load or no-load conditions, the characteristic frequencies shift close to fundamental (because the slip is very low), which leads to misinterpretation of fault signatures. Also, these frequency components can be superimposed by frequencies generated due to load fluctuations, voltage supply modulations or bearing defects.

In advance frequency-domain methods, the limitations such as the requirement of high-precision slip information in spectral analysis for accurate detection of fault harmonics have been addressed. Under low slip conditions, the desired fault frequencies can be suppressed by the fundamental frequency component [Tsoumas et al., 2008]. Therefore, high-resolution frequency estimation techniques are implemented. In [Jung et al., 2006], optimal slip estimation, proper sample selection and auto frequency search using the pre-processing technique is proposed. The use of maximum co-variance method (estimation of slip) and zoom-FFT has been proposed in [Bellini et al., 2008] for fault detection in IM. In [Kia et al., 2007], the authors have demonstrated the use of ZMUSIC based on MUSIC and zoom-FFT (ZFFT). The aim is to increase SNR in a given frequency bandwidth. Prony analysis has also been demonstrated for high-frequency spectral analysis of BRB faults [Chen and Živanović, 2010; Chen and Zivanovic, 2007]. In [Cupertino et al., 2004], MUSIC and short-time MUSIC has been used on voltages induced in stator windings. ESPRIT with simulated annealing algorithm is implemented to identify the amplitude and phase of BRB related frequencies in [Xu et al., 2012]. The implementation of ESPRIT on zero-sequence current is proposed for BRB fault detection [Morinigo-Sotelo et al., 2017]. The BRB fault detection using MUSIC has been implemented on the induction motor fed with variable frequency drive in [Singh and Naikan, 2018].

2.3.3 Time-frequency analysis based FDTs

The techniques related to the time-frequency domain are reported in recent review articles such as [Hassan et al., 2018; Mehrjou et al., 2011] and techniques including wavelet transform, [Samanta et al., 2018; Elbouchikhi et al., 2016; Naha et al., 2016; Garcia-Perez et al., 2011; Kia et al., 2007], Gabor analysis, Hilbert transform [Rangel-Magdaleno et al., 2017; Bessam et al., 2016; Aydin et al., 2011] have been reported. Time-frequency analysis provides solutions for non-stationary signals by dividing them into parts, thus assuming them as stationary and then applying frequency-domain methods. Wavelet transform (WT) is a powerful tool to obtain good time resolution for high-frequencies and frequency resolution in low frequencies; its comparison with FFT is reported in [da Costa et al., 2015; Lee et al., 2010]. The application of WT can be seen for the detection of broken bars fault diagnosis. The application of WPD is presented in [Ye et al., 2003], where the current signals are decomposed using WPD and analysed for different depths for BRB and eccentricity fault detection. Antonino et al. [Antonino-Daviu et al., 2006a,b] showed the time evolution of low-frequency fault frequencies by decomposing the start-up current signals using higher-order Daubechies wavelet. The energies of the low-frequency detail coefficients were shown to be higher in case of faults as compared to healthy. The application of DWT on start-up current signals is proposed in [Ordaz-Moreno et al., 2008], where a weighting function based on DWT is found to indicate the fault severity whose implementation is performed on low-cost FPGA. The fundamental component is suppressed using complex Morlet wavelet and its efficacy is proved by comparing with other window function; later fault index based on mean absolute deviation is proposed for fault detection [Tsoumas et al., 2008]. Reference [Kia et al., 2009] presented the broken bar fault diagnosis without slip estimation by computing energies of the detail coefficients obtained after current decomposition using DWT. The current signals are decomposed using *db44* for fault analysis using energy eigenvalues based on data-dependent and independent approaches in [Bouzida et al., 2011] for the detection of BRB and end-ring fault and for loss of stator phase. A novel fault index constituting an average of the detail coefficient (capturing frequencies near fundamental) and its fluctuation is proposed in [Ebrahimi et al., 2012].

In [Ebrahimi et al., 2012], specific frequency band detail coefficient is analysed and a fault index based on its absolute average and average fluctuation are proposed for BRB fault and its severity detection. The study based on wavelet coefficients of stator current within a specified frequency band is proposed in [Shi et al., 2014], where the fault criterion for determining the severity of broken bars is also based on speed ripple for various load conditions. In [da Costa et al., 2015], db-44 mother wavelet with 8 level decomposition is used for decomposing stator current signals. A method based on discrete harmonic wavelet and FFT of stator current is proposed in [Sapena-Bañó et al., 2015]. The DWT has also been applied on the spectrum of stator current signals to identify significant peaks which are further analysed using multivariate control charts in [García-Escudero et al., 2011]. Post-feature extraction using recursive un-decimated WPT, classification is performed using directed acyclic graphs (DAG) SVM for BRB fault diagnosis [Keskes and Braham, 2015]. In [Lamim Filho et al., 2018], the modulated components using empirical demodulation of pre-processed current signals are extracted whose decomposition is done using DWT and later analysed with orbit pattern inspection. Another time-frequency based technique i.e. frequency B-splines is proposed in [Pons-Llinares et al., 2011] for BRB fault, high resolution near the defect frequency is reported. In [Blodt et al., 2008], a time-frequency decomposition based on Wigner-Ville distribution has been used phase modulation (arise due to load torque oscillations) in stator currents. The reduced envelope signal is built for BRB fault diagnosis in [Sapena-Bano et al., 2015] to reduce the computational effort without losing the spectral information.

Another time-frequency analysis tool is Hilbert-Huang Transform whose application can be seen in [Antonino-Daviu et al., 2009], where the evolution of LSB component in start-up current is analysed by decomposition using Hilbert-Huang transform. The authors have also compared with DWT. Post-envelope detection using Hilbert transform of current signals, DWT is implemented for fault detection [Jimenez et al., 2007].

2.3.4 Machine Learning based FDTs

The authors in [Ayhan et al., 2006], extended the use of multiple discriminant analysis with ANN for BRB fault classification. Using time-domain features with the help of ICA and PCA is proposed in [Widodo and Yang, 2007], these features are in turn fed to SVM for fault classification. The use of ML techniques with time, frequency and time-frequency domain methods has been in focus for rotor fault diagnosis. The features from PSD of current signals are used for classification using Fuzzy min-max neural network in [Singh et al., 2013]. The application of spectral analysis and EMD is proposed in [Valles-Novo et al., 2015], where two features i.e. samples between zero-crossings and the time elapsed are used for classification with an implementation on FPGA. In [Garcia-Bracamonte et al., 2019], the authors proposed a BRB fault detection approach based on ICA of spectral information of current signals and it is auto-correlation such that standard deviation of a certain region of ICA signals is found to be useful. The use of Hilbert transform and SVM is proposed in [Matic et al., 2012], for one BRB fault detection. Self-organizing maps are used for BRB fault detection with the features extracted using WT [Germen et al., 2014]. The envelope of the stator current is extracted using Hilbert transform whose amplitude and frequency are used as input to ANN for BRB classification under different load conditions [Bessam et al., 2016]. In [Naha et al., 2016], the authors have used extended Kalman filter for determination of fundamental component and MUSIC for fault classification. In [Lizarraga-Morales et al., 2017], the

Table 2.3 : FDTs for BRB fault diagnosis

Technique used	Signal type	Classification using	No. of broken bars considered	Reference
Hilbert Transform	Start-up	-	1 BRB	[Abd-el Malek et al., 2018]
Empirical Mode Decomposition	Start-up	Hidden Markov Model	1BRB, 2BRB	[Georgoulas et al., 2013]
Frequency estimation (ESPRIT, MUSIC,)	Steady-state	-	-	[Trejo-Caballero et al., 2017; Trachi et al., 2016a; Singh and Naikan, 2018; Kim et al., 2012]
Rayleigh quotient with extended Kalman filter	Steady-state	-	Partial, 1/2BRB, 1BRB	[Samanta et al., 2018]
Zero sequence current	Steady-state	-	1BRB, 2BRB	[Gyftakis et al., 2015]
FFT and PCA	Hall effect sensor data	ANN, k-NN, SVM	One to many	[Dias and Pereira, 2018]

features are extracted using homogeneity analysis and then classified using Gaussian probability density function. With the help of features from WPD of current signals, the use of multiple AFNIS for classification is proposed to reduce the time and computational complexity of the training [Ye et al., 2006]. An application of WPD and ANN is reported in [Sadeghian et al., 2009], where current decomposition is performed till selective levels; whose features are fed to ANN for classification of BRB faults. In [Bessam et al., 2015], WT and HT are used for feature extraction which is further used with linear discriminant analysis for fault classification. The authors in [Liboni et al., 2019], the currents signals are decomposed using orthogonal component decomposition and the features extracted are fed to SVM for BRB fault classification. In [Bacha et al., 2012], Hilbert modulus and phase current space vector are analysed using FFT and then features are extracted using SVM for BRB and other faults detection. FDTs for BRB fault diagnosis are also listed in Table 2.3. Table 2.4 highlights the characteristics of popular signal processing techniques used for fault diagnosis of stator, bearing and rotor faults. The advantages and shortcomings of various artificial intelligence techniques used in designing fault diagnosis algorithms are also provided in Table 2.5.

2.4 RESEARCH GAPS

There are many applications of signal processing based methods which are found to be successful in diagnosing the fault. The research gaps in the current literature are:

1. An algorithm that deals with locating the faults such as in bearings (fan-side or load-side) have not been proposed yet.
2. The research reported is based on the emulation of the bearing faults not the actual faults.
3. Intricate machine learning strategies (e.g. feature selection/reduction) are yet to be explored for fault diagnosis algorithm for the induction motor.

Table 2.4 : Comparison between some popularly used techniques for FDTs

Technique	Characteristics	Shortcomings
FFT	Simple and easy to implement;provides clear information of frequency characteristics	Limited for stationary signals; provides global frequency information; not localized in time-domain; require larger samples for high frequency resolution; side-lobe leakage
Spectral estimation techniques	High-frequency resolution	Computationally expensive; requires longer time
STFT	Linear TF analysis technique; provide time-localization	Dependent on type and length of window; resolution in either time or frequency domain is a trade-off
Wigner-Ville and its variants	High-frequency resolution, smooth window application	Presence of cross-interference frequencies indicating the presence of noise
WT	varying window sizes for low/high frequency resolution, detection of transients	Choice of mother wavelet is still a not a direct task, difficult in understanding the spectra
HHT/EMD	Decomposes as mono-component oscillations	EMD is sensitive to break-points (start and end)
AI based tools	No mathematical model required; easy implementation	Training requires large amount of data; validation is must

Table 2.5 : Comparison of machine learning techniques used in the literature for FDTs

Learning technique	Parameter Estimation Algorithm	Features	Shortcomings
Artificial Neural Network	Gradient Descent Algorithm	ability to learn and model non-linear and complex relationships, good generalization	overfits model for small data, require large dataset for generalization
Support Vector Machine	Quadratic optimization	good generalization capability for smaller datasets, less computational time, proper chosen kernels performs well	choice of kernel is difficult, high algorithmic complexity, high memory requirement
K-means Clustering	k-means algorithm: performs iterative calculations to optimize the positions of the centroids	unsupervised algorithm; does not require training/testing data	choice of k is critical; only deal with numeric data; hard clustering method
Naves Bayes Classifier	Bayes theorem; assuming that features are independent and their covariance is zero	fast and easy to implement	Incomplete training data: Collapses when unseen case occurred (assign zero probability there)
k-nearest neighbour	Parameter Tuning with Cross Validation	robust and versatile method; non parametric and instance-based learning algorithm	Minimal training but expensive testing; Huge Memory Cost
Bayesian network	Expectation Maximization Algorithm	no over-fitting	computationally expensive, works poorly with high dimensional data
Gaussian Mixture Model	Maximum Likelihood Estimation (MLE) by EM Algorithm	soft clustering method; based on Gaussian distribution	not applicable for intrinsic representation of high-dimensional data
Hidden Markov Model	Baum–Welch algorithm	statistical markov model with hidden states; strong statistical foundation; efficient learning algorithm	being generative model it requires large dataset