



Condition monitoring of Induction motors through Simulation of Bearing Fault and Air Gap Eccentricity Fault

Priyanka, Neelam Turk, Ratna Dahiya

Abstract: Induction motors have an important role in the industry on account of their advantages over other electrical motors. Consequently, there is a huge demand for their safe and sound operation. But it is not free from failures, which result in unnecessary downtimes and create great losses with regards to both revenue and maintenance. For that reason, early fault detection is considered necessary for the safety maintenance of the motor. In the present circumstances, the health monitoring of the induction motors are progressively increasing due to its potential to enhance operating costs, increase the reliability of function and so does the current paper emerge. Also, this paper deals with a novel effective technique for detecting the bearing fault and air gap eccentricity fault of the induction motor. Summarization and analysis of the findings are done based on percentage error and fitness function Value. Comparison results of bad bearing faults and air gap eccentricity are given separately in the paper. The findings of the study concluded that particle swarm optimization (PSO) can be considered as better optimization for bad bearing fault whereas modified particle swarm optimization is concluded as better optimization for air gap eccentricity fault.

Keywords: Air Gap Eccentricity Fault Simulation, Bad bearing Fault Simulation, Condition Monitoring, Induction Motor, Particle Swarm Optimization

I. INTRODUCTION

Though induction motors are reliable and strong, it is not free from failures and might give rise to production loss or risky operating conditions. Condition monitoring is broadly applied to discover and diagnose machine faults prior to they end up at an unacceptable level. There are large number of commercial tools available and conventional techniques to examine the condition of induction motors and related machineries. Many condition monitoring techniques are not absolutely cost-effective for induction motor driven systems. Nevertheless, essential induction motor applications are to be found in all industries and induction motors of an extensive range of horsepower ratings are utilized. The techniques most frequently used in condition monitoring integrate vibration analysis, thermo-graphic monitoring, scientific modeling and signature analysis.

One or a blend of these methods could be employed to discover and analyze motor electromechanical faults and failures on the driven load Pole and Holifield (2011). An induction machine has an important role in engineering or production process and consequently there is a huge demand for their consistent and cautious operation. In general, they are considered reliable but in the end do exhaust.

Faults of induction machines could result in extreme downtimes and create huge losses with regards to repairs and lost profits, and this encourages the inspection of on-line condition monitoring. Also, in terms of condition based maintenance, it is not possible for one to schedule maintenance on the basis of existing records or geometric estimations of machine failure. Relatively, one can rely on the information delivered by condition monitoring techniques evaluating the machine's condition. Therefore an important element for the accomplishment of condition based maintenance is holding a perfect and an appropriate means of condition appraisal and fault diagnosis Sin, et al (n.d.).

The greater part of electrical machines employs ball bearings and these are considered as one of the most frequent causes, which results in failure. These bearings include an inner and outer ring in addition to a collection of balls or rolling elements positioned in shafts revolving inside these rings. The primary pace for condition monitoring and defect diagnosis is to build an analysis technique which could be employed to diagnose the perceived existing signal to obtain useful information Dlamini, (2014).

Fault detection of induction motors includes two fundamental components, i.e. feature extraction and classification. The underlying principle of feature extraction is to extract features that are associated with specialized fault techniques. Generally the features are extracted by processing the range of stator current of the induction motors applying Fast Fourier Transform (FFT). The errand of differentiating defective conditions from usual conditions on the basis of the resulting FFT spectrum could be carried out precisely as far as the signals are static, the induction motors are progress around full-load setting, and the terminal energies are sinusoidal. There are various signal processing methods that are extremely helpful for fault diagnosis function. These include Fast Fourier Transform (FFT), time-Frequency techniques, wavelet transform, and time series method such as Welch, MUSIC method and paradigm. (Mehala et al, 2017). Induction motor has an important role on account of their benefits over other electric-powered motors. If any failures occur in the motor it could result in extreme downtimes and produce great losses with regards to revenue and maintenance.

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* Correspondence Author

Ms. Priyanka*, Assistant Professor, Department of Electrical Engineering, YMCAUST, Faridabad-121006

Dr. Neelam Turk, Associate Professor, Department of Electrical Engineering, YMCAUST, Faridabad-121006

Dr. Ratna Dahiya, Professor, Department of Electrical Engineering, National Institute of Technology Kurukshetra, Haryana (INDIA)-136119

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For that reason, advance fault detection is considered necessary for the motor protection. In the present state, the induction motor's health monitoring are progressively increasing as a result of its potential to lessen maintenance costs, improve the consistency of function and enhance service to the customers. In general, various failures of induction motors are categorized as either electrical or mechanical failures. Various categories of faults include stator winding faults, misalignment and bearing gearbox failures. The most widespread fault categories of these rotating machines have always been associated with the machine rotor. Noise in electrical machines is initiated by forces that are of magnetic, motorized and aerodynamic source. As well, the vibrations could generate on account of the inter-turn winding faults and single phasing Siddiqui, et al (2014).

The single-phasing will possibly take place on account of a fuse blowing or protecting tool unlocking on one phase of the motor. Other potentials integrate feeder or step-down transformer fuses blowing. Once balanced or slighting unbalanced energies are fixed to a three-phase induction motor then the specific motor will impart power to the shaft load. The motor will work within its evaluation while the voltages are being balanced. On the other hand, when the voltages turn into unbalanced extreme heating will take place and it is essential for the motor to be de-rated. In terms of the open phase on the step-down transformer, generally it will not be an inclusive protective scheme, which will separate the transformer store from service. The three "single-phasing" cases exhibit the essential demand for a protective system, which will separate the motor in any of these cases. The demand for the protective system is as well considered necessary once the supply voltages turn out to be unbalanced Kersting, (2005).

As a result of the strong association between motor system and bearing assembly functioning, it is quite complicated to assume the progression of contemporary rotating machines without concern of the extensive application of bearings. Besides, the faults appearing in motors are frequently associated with fault bearings. In many cases, the accurateness of the machinery and devices used to detect and monitor the motor system is largely reliant on the effective performance of bearings (Saadaui et al, 2011). Bearing defects could take place due to fatigue of their material in standard operational conditions. Distributed and localized defects are two important parts of bearing faults. Distributed defects have an effect on a whole region and are complicated to distinguish by different frequencies. On the contrary, single-point flaws are restricted and are categorized in line with following affected element, which include outer and inner raceway defect and as well ball defect in different load and transitory setting Ibrahim and Nekat (2013).

Contamination and deterioration recurrently increase bearing failure speed on account of the rough environment exhibit in a large amount of industrial settings. In general, installation issues are often induced by reprehensively coercing the bearing onto the shaft. This generates physical impairment in the form of false brinelling of the shafts, resulting in premature failure. As well, misalignment of the bearing is a common effect of imperfect bearing installation. Bearing faults could be categorized to single point faults and comprehensive roughness faults. In both instances, flaw related frequency elements are adapted with the basic occurrence in stator current. Based on the location of the

flaw, bearing faults could be categorized into three, which include ball fault, inner and outer race fault. However, this categorization does not integrate all bearing faults. Also, the two categories involved in bearing faults are single point faults and generalized roughness failures Wang, (2007).

Operation, reliability and effectiveness are of the most important concerns application of induction motors. Recent studies exhibit that around 40% of faults in electrical-centric machines are associated with their ball bearings (Haddadnia, 2014). Consequently, if process of formation progression of this type defects could be noticed at initial stages; damages can also be prevented. Created flaws in ball bearings are generally restricted that subsist in inner and outer rings and case-shots. Generally, vibration signal is the tool that detects faults in ball bearings. In recent decade, more highly developed techniques for example wavelet transform (WT) (Zarei, 2005) and wavelet packet bearing (Zarei, 2007), have been employed for Flaw detection of ball bearings. The techniques have increased calculation volume; moreover they necessitate having an experienced and trained personality for the detection of system status (Haddadnia, 2014).

In an induction motor many faults might take place concurrently and in that case grit of the primary problem is quite complicated. Overload, overvoltage, undervoltage, single phasing, and voltage unbalance are some of the external motor faults. As the mechanical overload on induction motor intensifies the motor sets to draw increased current and speed fall. After specific quantity of load heat generation ratio is greater than heat indulgence ratio than the insulation is exposed. Overload protection is constantly fixed to motors to keep them away from overheating. Induction motor is meant to resist overvoltage around +10% as common voltage design motor manufacture requirement. Single phasing is the most terrible instance of voltage unbalance and could be taken place on account of open winding in motors or some open circuit in some part anywhere between the secondary of transformer and the motor or opening of fuse. The single phasing sets off unbalanced currents to flow and the destructive sequence element of these unbalanced current results in the rotor to overheat Huang, (2005).

Electrical machines and drive systems together are exposed to various kinds of faults. (Fig.1, Yeh, et al 2008). Stator faults, rotor faults, mechanical faults including bearing damage, eccentricity and misalignment and defect of one or more power electronic elements of the drive system are some of the faults involve in this. Induction machines are considered as symmetrical machines to large extent, so any kind of fault adapts their balanced properties. Characteristics fault proportions consequently emerge in the assessed sensor signals, based on the type of fault. Bearing fault is considered as the main contributor for fault in a three-phase induction motor, which is classified as a mechanical fault. Around 40-50% of induction motor defects are associated with mechanical defects. Categorization of these flaws integrates fault in rolling element bearing and eccentricity Pandey, et al (2012).

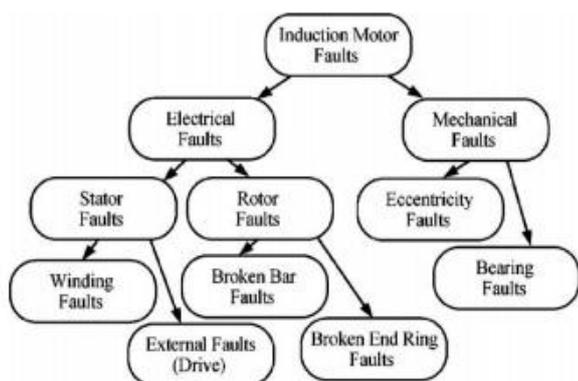


Figure 1: Classification of induction motor faults
Source: Yeh, et al (2008).

Induction motors could be uplifted from consistent frequency sine wave energy supplies or from adaptable speed ac drives. Though, induction motors are increasingly exposed to defects once supplied by ac drives. This is as a result of the increased voltage pressure on the stator windings, the increased ratio stator current constituents, induced by ac drives. The motor faults are taken place as a result of mechanical and electrical pressures. Mechanical stresses are induced by overloads and sudden load variations, which could generate bearing faults and rotor bar defect. Conversely, electrical stresses are generally related with the energy supply. In terms of internal faults, coil movements, bearing defects, rotor strikes and eccentricity are some important faults while external faults are pulsating load, overload, electrical transient energy and unbalanced voltage. In general, broken rotor bars do not make an induction motor stop working; however there could be intense secondary consequences of broken rotor bar. These broken elements of rotor bar strike to the stator core of an increased voltage motor at an increased velocity. Pulsating mechanical loads, for example, reciprocating coal crusher could expose the rotor cage to increased mechanical pressures Gupta, et al (2014).

Bearing faults are considered as the main contributor of failures with 40% ratio in total motor failures. Contamination and deterioration recurrently increase bearing failure speed on account of the rough environment exhibit in a large amount of industrial settings. Bearing faults could be categorized to single point faults and comprehensive roughness faults. In both instances, flaw related frequency elements are adapted with the basic occurrence in stator current. Singh and Shaik (2018) pointed out that bearing defects stimulate vibrations in the machineries, consequently resulting in expected ratios in the vibration spectrum. Also, these vibrations disturb the air-gap eccentricities that trouble flux density. It influences the stator current that could be obtained in its spectrum.

Three phase induction motors are largely employed in the industry and diagnostic techniques for such motors are critical. One of theoretical points regarding motor current signature analysis (MCSA) is that sensing an electrical signal is possible, which includes existing elements that are a direct consequence of distinctive rotating flux constituents produced by faults for example broken rotor bars, bad bearing, air-gap eccentricity, etc. It is possible for MCSA to find out these issues at an initial phase and consequently prevent secondary fault and complete defect of

the motor. It is evident that broken rotor bars would cause a variation to the vibration spectrum; however vibration is usually can be sensed at the bearings. Also, for every motor there is a unique mechanical rigidity between the electromagnetic forces produced by broken bars and the place where the vibration is being sensed. Findings obtained by Glowacz, et al (2017) emphasized that MCSA has that potential to sense the defects a phase-to-earth faults in advance.

Aathikessavan, (2019) dealt with detecting failures in induction motors, in particularly with BRB detection. The BRB fault is one of the major fault forms of induction machines, for instance, Motors. The effects of this failure integrate extreme vibrations, weak poor starting performances, and increased thermal stress. The findings emphasized that if this failure is undetected it may result in potentially catastrophic malfunctions. Accordingly the study put forward that it is significant to find out this specific imperfection to prevent lasting failure of induction motors. And MCSA is one of the prominent techniques to detect the BRB fault.

Air-gap eccentricity is considered as one of the most widespread categories of fault taking place in the induction motor (Moosavi and Faiz 2016). This kind of fault results in uneven air-gaps between the stator and rotor that actually has a bad impact on the output rotation accurateness of the motor. With the intention of detecting the eccentricity fault, various kinds of techniques are employed, for example the monitoring of magnetic flux and vibration (Liu and Bazzi 2017). Though, as a result of the increased cost and complicated investiture of sensors, the abovementioned techniques are comparatively less suggested. Over the last decade, MCSA (Verucchi, et al 2016) is broadly employed to identify the defects in the electrical machine, since the stator signal is comparatively simple to acquire and never demand additional compound and high-priced sensors. In line with the hypothetical models, the spectral constituents associated with fault can be sited (Saucedo-Dorantes, et al 2016). The incidence of air-gap eccentricity could institute the specialized harmonic element in the stator current field.

The *raison d'être* that initiate eccentricity are defined as follow (Nandi, et al 2002): Function of the motor at decisive speed; wrong placing of rotor and stator during manufacturing process; mechanical resonance at essential load; wrong placing of rotor shaft; corrosion of ball bearings. Any variation from the normal function of the motor that could be assessed could act as fault index for recognition and diagnosis of defects and damages. The single-phase instant energy has been suggested for the analysis of mixed rotor faults (Liu, et al 2004). Both simulation and experiential findings exhibit the efficiency of the partial power and also the total direct power approach. Air-gap eccentricity in induction motor results in characteristic harmonic elements in electrical and mechanical magnitudes. In addition, the usage of the compound apparent energy for the recognition of air-gap eccentricity setting gives concurrent information regarding the voltage, which could be of principal importance once in the occurrence of an uneven supply voltage system Drif and Cardoso (2006).

Air gap eccentricity is one of the most important faults taking place in machines and its detection can be useful for inhibiting potential tragic failures. If this kind of defect is not resolute, it would result in the rotor–stator rub and accordingly defect of the whole motor. There are three categories of eccentricity, which include static, dynamic and a mixture of both, which is known as mixed eccentricity. In the majority of cases, both static and dynamic concurrently take place. Study by Reda, et al (2017) exhibited that the energy level intensify concurrently with the increasing level of the eccentricity defect.

Generally, air-gap eccentricity technique for induction motor is categorized as static and dynamic eccentricity, and also combined eccentricity of these two categories. In the case of static air-gap eccentricity, statistical axis of rotor's rotary motion is not the statistical axis of the stator, and setting of the least radial air-gap length is set in space. In terms of dynamic air-gap eccentricity, the rotor revolves on all sides of the geometric axis of the stator, wherein the location of the minimum air-gap length revolves with the rotor. Induction motor air-gap eccentricity faults could cause unbalanced magnetic pull, bearing fault, extreme vibration and noise, and also stator-rotor rubs defects (Zhang, et al 2011). Blödt et al (2009) dealt with a Wigner distribution technique in order to examine stator current signals and analyze induction motor eccentricity defect. Akin et al. (2011) carried out real-time eccentricity fault recognition employing reference frame concept. Bossio et al (2006) used added excitation to exhibit information on the subject of air-gap eccentricity fault. On the basis of the motor specification, the instituted air-gap eccentricity flaws are regarded as the primary phase of the induction motor fault Wang and Ismail (2017).

The air-gap eccentricity defect has been analyzed in the transitory condition by time-domain and also time-frequency domain methods with the assistance of a recommended dynamic simulation model (Siddiqui, et al 2016). The low-frequency estimation signal diagnoses the eccentricity defect in the transitory condition. Consequently, advanced fault diagnosis of the induction motor is feasible and prevented the motor before reaching the harmful cases. Consequently, the industries might keep large revenues in hand and prevent unanticipated failure conditions. The mainstream of the defects in three-phase induction motors have correlation with air-gap eccentricity that is the setting of the uneven air-gap amid the stator and the rotor. This fault could rise from large number of sources for example inaccurate bearing positioning in assembly, a shaft diversion, heavy load, etc. Generally, there are two types of air-gap eccentricity, which include radial and axial. All of them could be static or dynamic eccentricity (Siddiqui, et al 2016).

II. LITERATURE REVIEW

Misra and Agarwal (2017) pointed out that induction motors has a significant role in the industry and accordingly there is a huge demand for their consistent and harmless operation. This study gives an all-inclusive concept of different faults, their basis, detection techniques, and most recent trends in the condition monitoring technology. This technology could contribute to enhance the reliability and lessen the maintenance expenditure of induction motors. As well, this research can be employed as a clear guide to future scholars

in the field of monitoring and assessing electrical machines. This report investigates the existing developments in on-line fault detection and analysis of induction motors. Besides, this study has given the practical applications of the MCSA employed for induction motors defects detection. A transitory assessment of the most important electrical defects in case of induction motors has been reviewed here presenting the state-of-art developments in the finding and diagnosis of these defects.

Vinothraj, et al (2018) stated that diagnosis of defects in induction motor is a central process in industrial plants to enhance the consistency of the machine and lessen the financial loss. Amongst the different defects taking place in induction motors (IM), bearing fault is considered as the major one that includes almost 60% of faults. In this review, an analysis of the induction motor with bearing fault feed from a three phase voltage source Pulse Width Modulation (PWM) inverter in open loop has been performed employing Finite element method (FEM). The occurrence of bearing fault could be obtained from the spatial FFT band of radial air-gap flux intensity. The following specification will result in bearing faults in induction motor, i.e. poor lubrication, contagion, resistance and electrical pitting that take place particularly in inverter fed machines. Once the corrosion in the bearing increases, the current ripple also gets intensified that result in torque wave and lessen in average speed.

Sudha and Anbalagan (2009) reviews a protection system for three-phase induction motors from incipient defects through embedded microcontroller. It is true that the induction motor is subjected to various kinds of electrical faults including over and undervoltage, overload, unbalanced voltage and single-phasing. On account of these electrical defects, the windings of the motor is likely to get overheated that result in insulation defect and therefore lessen the motor's survival. To examine the performance of induction motor in electrical defects, the induction motor is developed employing arbitrary reference system in MATLAB environment; the defects are produced and the difference of the induction motor factors in defective conditions are obtained. Derived from the analysis, embedded controller is formed to look after the motor from incipient defects.

Siddiqui and Sahay (2016) deals with a new efficient technique for establishing the air-gap eccentricity defect of the induction motor. Appropriate means for condition monitoring will possibly enhance the consistency and lessen the maintenance expenses of induction motors. Also, condition monitoring is likely to include sampling sensor signals, dealing out with these signals in order to wheedle out features that are receptive to the existence of faults, settling if a fault occurs and finding its type. The motor stator current signature analysis technique has been employed to differentiate healthy and also defective conditions of the induction motors with competitive cost. The fault might be prevented before reaching in the catastrophic settings and accordingly industrial plants might save large proceeds and unpredicted shutdown.

As stated by Kande, et al (2017) induction motors are exposed to incipient defects which, if unnoticed, could result in critical machine failures.

Condition Monitoring (CM) is a method of obtaining equipment health condition and forecasting the operational capability of a structure in a given environment: Motivations for CM in industrial automation integrate depletion in downtime, protection activity and associated faults, and rise in energy effectiveness and quality. The study reviews existing machine CM techniques and industrial mechanization for plant-wide CM of rotating electrical machines. Cost and complication of a CM system intensify with the quantity of dimensions, so wide-ranging condition monitoring is at present largely limited to the settings wherein the effects of poor accessibility, quality are so critical that they evidently rationalize the investment in monitoring. One of the most important restraining factors is the proportion of CM cost to equipment cost that is fundamental to the recognition of employing monitoring to direct maintenance for a greater fleet of electrical machines. The results put forward that long-standing service life, low expenditure, and effective or informative fault indication are some of the primary characteristics for the development of condition monitoring techniques.

Alwan, et al (2017) reviews the impact of the static air-gap eccentricity on the functioning of a three-phase induction motor. The Artificial Neural Network (ANN) technique has been employed in the study to identify this defect. This technique is based on the magnitude of the positive and negative concordant of the frequency. MCSA derived from stator current has been employed to find eccentricity defect. Feed-forward neural network training algorithms are utilized to carry out the motor fault detection. The efforts of ANN are the amplitudes of the positive and negative harmonics, and the output is the kind of fault. The progression of neural network is accomplished by data by means of the experiments test on both healthy and defective motor and the diagnostic structure could distinguish between “healthy” and “defective” machine. From the abovementioned faults: the stator, broken rotor bar, eccentricity faults and bearing faults are considered as the most widespread ones and therefore necessitate special attention. Therefore, the findings put forward that these faults and their diagnosis methods should be investigated briefly in the near future.

III. EXPERIMENT AND SIMULATION OF THE PROPOSED SYSTEM:

a. Bad Bearing Fault:

In induction motor a common fault is ball bearing and it is primarily due to the abnormalities of mechanics in assembly. This study proposes that the values of bearing problem for around 40 percent of the failures in machine. The fault of bearing are very critical for the electromechanical machine functioning and for this reason the examination for the same is very essential. The fault of bearing are generated due to the ball defect, outer race defect and inner race defect. The faults of bearing will impose frequencies of characteristic fault into magnetic flux density of stator and evolved detectable vibrations. The fault frequencies magnitude is very small particularly at fault's initial stage. Every particular fault results the harmonics at a particular characteristic frequency in magnetic flux and stator current. Those frequencies are the motor characteristics data functions and conditions of operation and indicate the specific fault signatures. In the stator

current the frequency for the signatures of bearing fault can be indicated by:

$$f_b = |f_s \pm k \cdot f_c| \tag{1}$$

Where $k=1, 2, 3, \dots, f_s$ is the frequency of supply and f_c is the frequency of fault. In Bad Bearing Fault first a test bench was set up comprising the materials bill in the below table 3.1:

Table 3.1: Test Bench Materials Bill
Source: Author

| S.No. | Part | Specification | Make |
|-------|--------------------|--|---------------|
| 1 | Ammeter | EQ9630A(X2) | RISHABH |
| 2 | Circuit Breaker | NC, 310N C10 | HAGER |
| 3 | DSO | DSO-3204-X | Agilent |
| 4 | Motor | 3PH, 440V, 1.5KW, RPM-1395/157 | SEW-Eurodrive |
| 5 | Connecting Cables | 0.5mm shielded cable for signals and three core 1.5mm for motor connection | ---- |
| 6 | Power Supply | 5V DC | ----- |
| 7 | Search Coil Sensor | XPT Series | Rogowski |
| 8 | Terminals | 1.5mm | Jainsons |
| 9 | Multimeter | True RMS | HioKi |

In the test bench the motor used was having the parameters which are mentioned in the below table 3.2:

Table 3.2: Specification of Induction Motor
Source: Author

| Specification | Motor |
|------------------|--------------|
| Current | 5.90/3.40A |
| Capacity | 1.5Kw/2.01hp |
| Frequency | 50 Hz |
| Efficiency | 79.6% |
| Voltage | 380V-460V |
| RPM | 1395 |
| Brake Type | M4B |
| Full Load Torque | 20Nm |

The below figure shows the SEW Euro Drive Motor with Name Plate:



Table 3.3: Expected Frequency of Inner race fault condition

| Condition of Load | K | Speed | Slip | Expected Frequency (Hertz) | |
|-------------------|---|-------|------|----------------------------|-------------|
| | | | | LSB (Hertz) | USB (Hertz) |
| No Load | 1 | 1395 | 0.07 | 61.6 | 161.6 |
| No Load | 2 | 1395 | 0.07 | 173.2 | 273.2 |

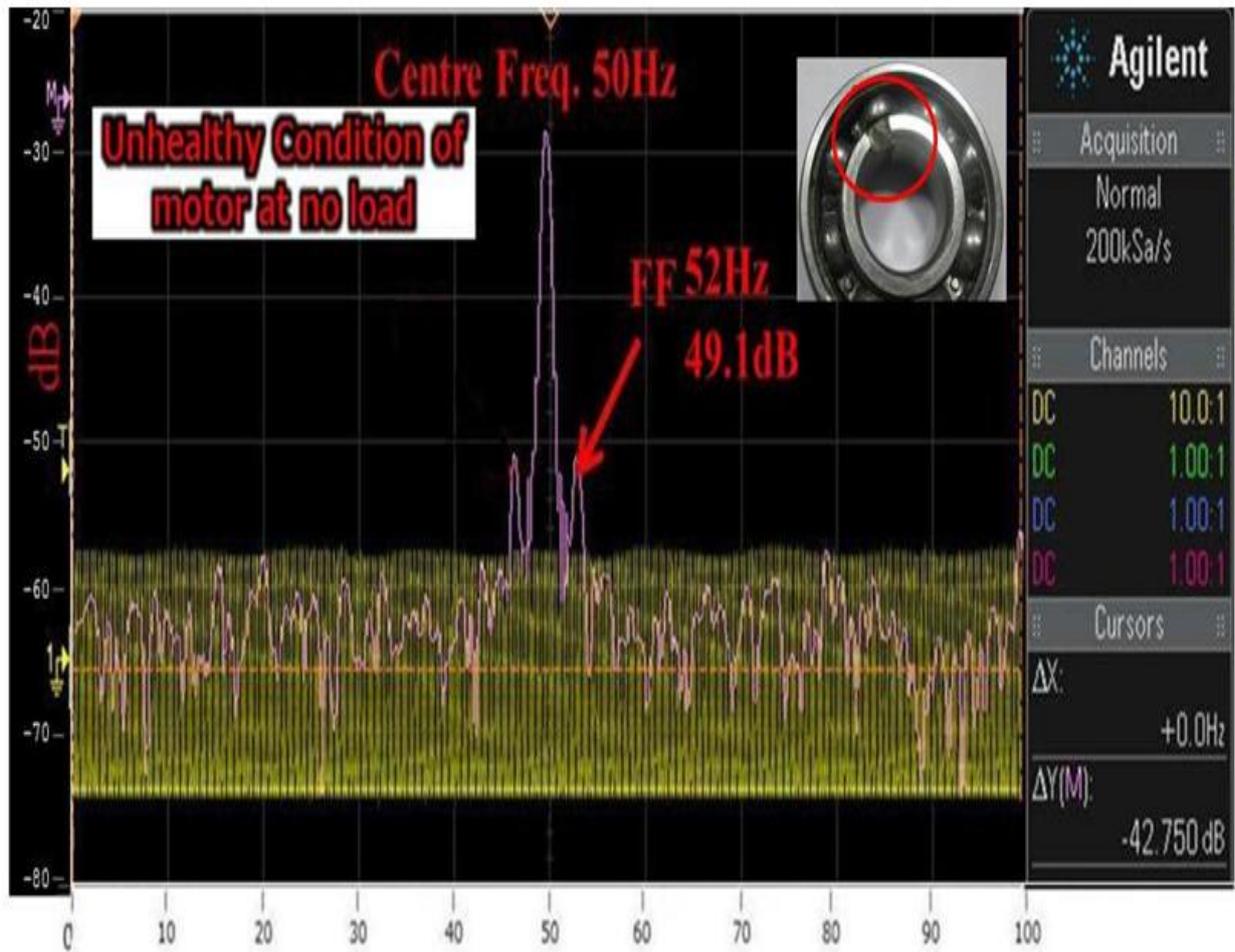
The results of a SEW-Euro Drive Motor are depicted in the below figure:

Figure 3.4: Spectrum for a SEW- EuroDrive Motor in healthy condition with no load



The signal with yellow color indicates the time domain signal and signal with white color indicates the frequency domain signal of the healthy induction motor. The center frequency is considered as $f=50$ hertz and the bands with slip side are less visible in healthy motor case. The bearing fault is made by destructing the bearing's inner race (2mm deep) and then it is applied in the motor. Then the spectrum is supervised and it was predicted that the fault frequencies are visible with 49.1decibel amplitude as compared to a healthy motor spectrum as shown in the below figure:

Figure 3.5: Spectrum for a SEW-Euro Drive Motor in Unhealthy condition with bearing fault of inner race



The rapidly developing personal computers computational supremacy permitted researchers to implement low cost but effective algorithms of optimization to assure the induction motors optimum parameters and supervise the induction motors health. PSO is very familiar among the optimization. Now MPSO (modified particle swarm optimization) and PSO (particle swarm optimization) are employed for approximation of parameter that is to optimize the condition back to healthy one and for the comparative research. The experiments are finished on 1.5-kilowatt, 440 volt, SEW Euro Drive induction motor and assessment of parameter is completed through the algorithms of MATLAB/Simulink.

i. Optimization and Simulation:

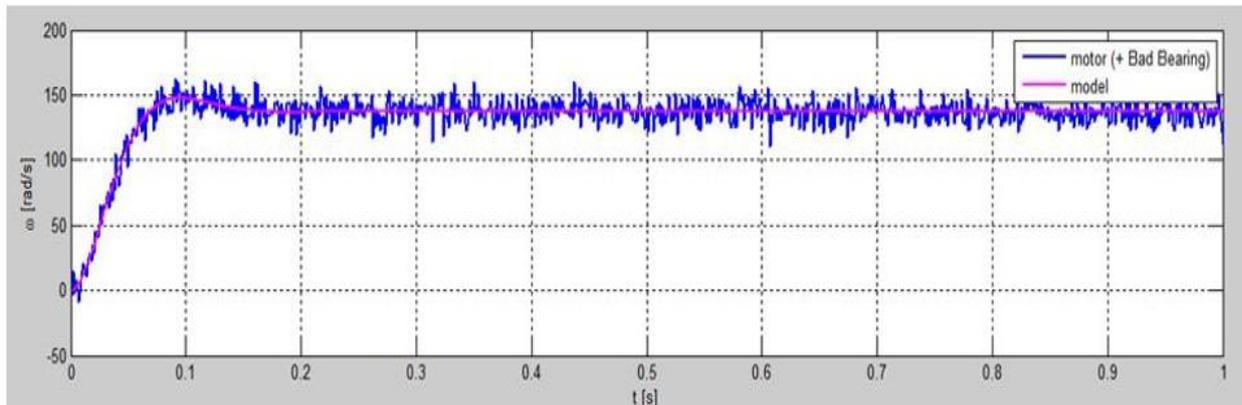
For the purpose of simulation, the similar set up of hardware has been employed in the algorithm and then the frequencies of fault [USB=161.6 Hz and LSB=61.6 Hz] associated to bad bearing fault are considered as range of reference to optimize the induction motor faulty behavior. Applying the MPSO and PSO on the following parameters of motor and later the results are combined through SIMULINK/MATLAB:

| Parameters of Test motor | |
|--|--------------|
| Ua= Rated Armature Voltage [V], | 420 Voltage |
| Mm= Rated Torque [Nm], | 20 nanometer |
| I = Rated Current[A], | 3 Ampere |
| Ra = Resistance of Armature Circuit [Ohm], | 0.177 ohm |
| La = Inductance of Armature Circuit [H], | 0.00334H |
| N = Rated Speed [RPM], | 1395 |
| W = N * pi/30; Rated Speed [rad/sec] | |
| Jr = 1.4; Inertia Moment [kg * m ²] | |
| Phi = (Ua - Ra * I) / W; Flux | |
| Ct = 3; Coefficient of Viscous Damping [Nanometer/rad/sec] | |
| USB = 161.6 hertz | |
| LSB = 61.6 hertz | |

Now with the Modified Particle Swarm Optimization and Particle Swarm Optimization the simulation is performed and bearing fault is made. The below figure 3.6 shows the faulty condition behavior in Particle Swarm Optimization and MPSO:

Figure 3.6: Simulation of PSO for a SEW EuroDrive Motor in Unhealthy condition with inner bearing fault at zero iteration

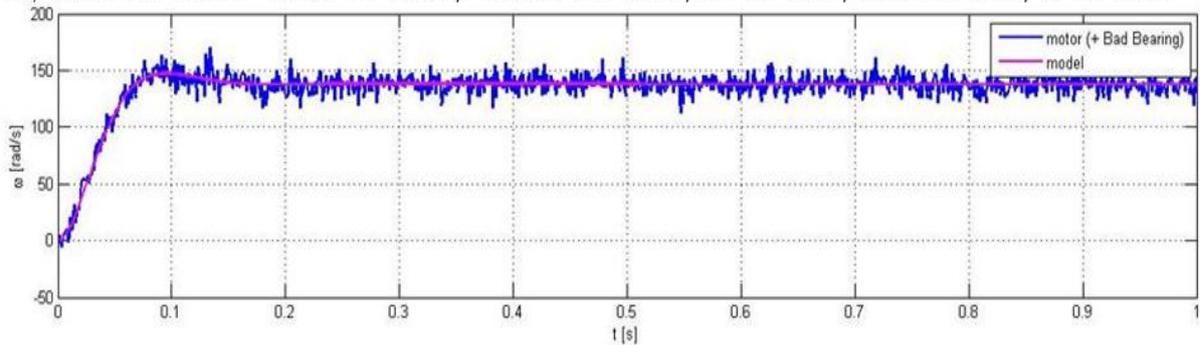
(1/80) Motor vs. ident: 0.177 vs. 1.278, 0.00334 vs. 0.289, 1.4 vs. 3.05, 2.87 vs. 4.96, 3 vs. 2.16



Another figure shows the faulty condition in MPSO:

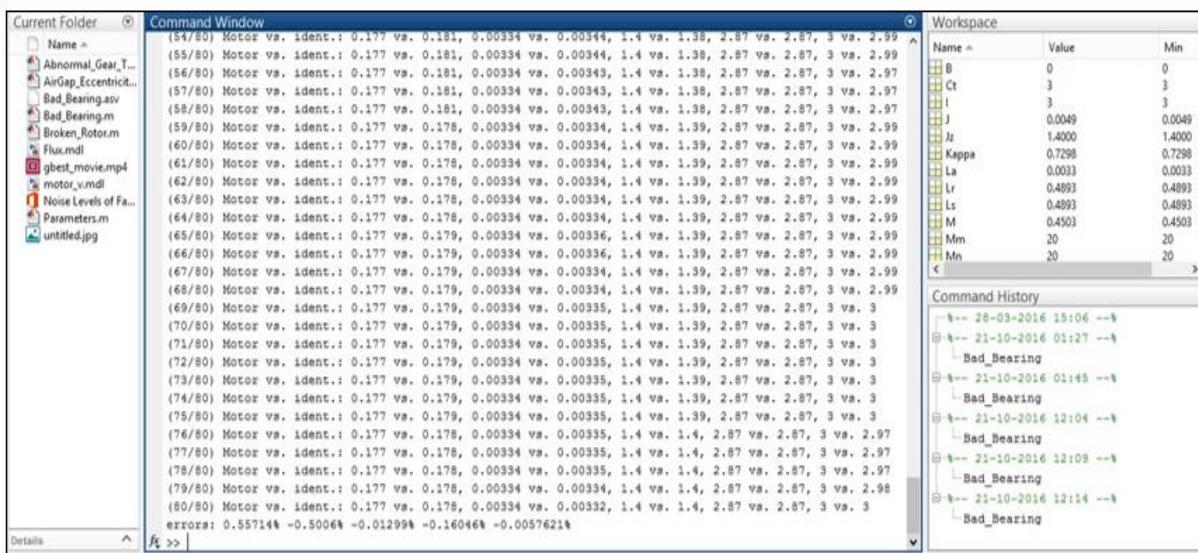
Figure 3.7: Simulation of MPSO for a SEW EuroDrive Motor in Unhealthy condition with inner bearing fault at zero iteration

(1/80) Motor vs. ident: 0.177 vs. 0.001, 0.00334 vs. 0.019, 1.4 vs. 2.85, 2.87 vs. 4.36, 3 vs. 6.16



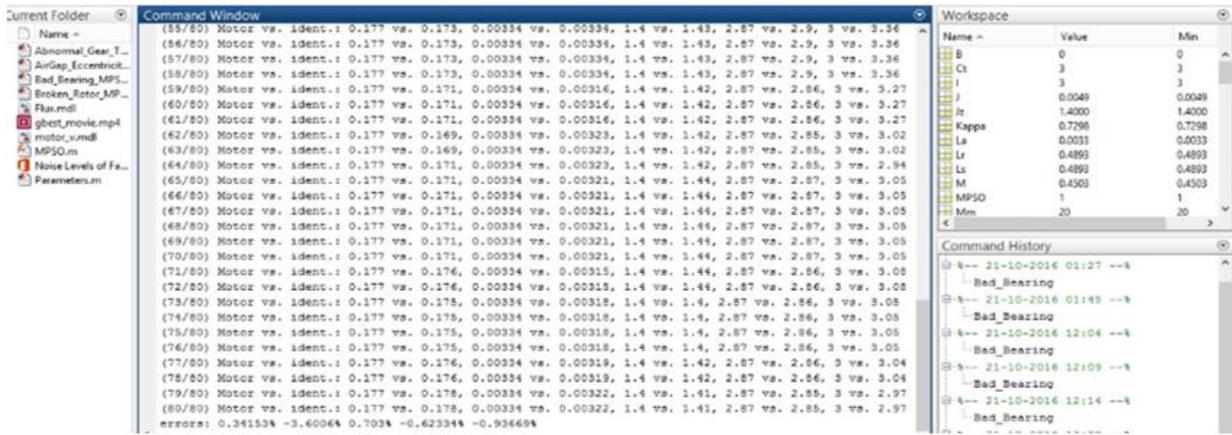
The below figures show the parameter convergence till 80 iterations. The figure 3.8 shows the error convergence using PSO:

Figure 3.8: Error convergence using PSO



Another figure shows the error convergence using MPSO:

Figure 3.9 Error convergence using MPSO

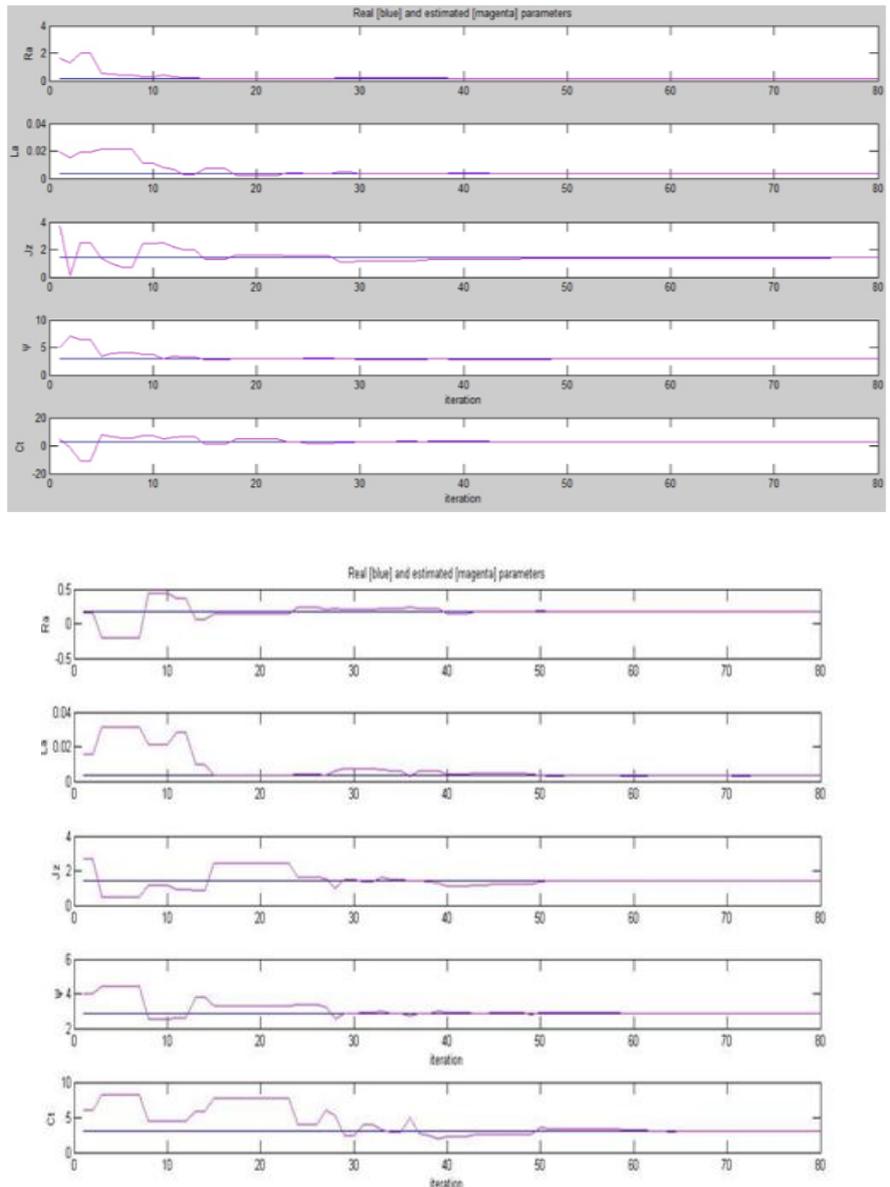


3.1.2 Results of Bad Bearing Fault:

The comparative research between the results of PSO and MPSO is carried out to verify the proposed method

effectiveness. The below figures show the results of all parameter optimization using MPSO and PSO respectively.

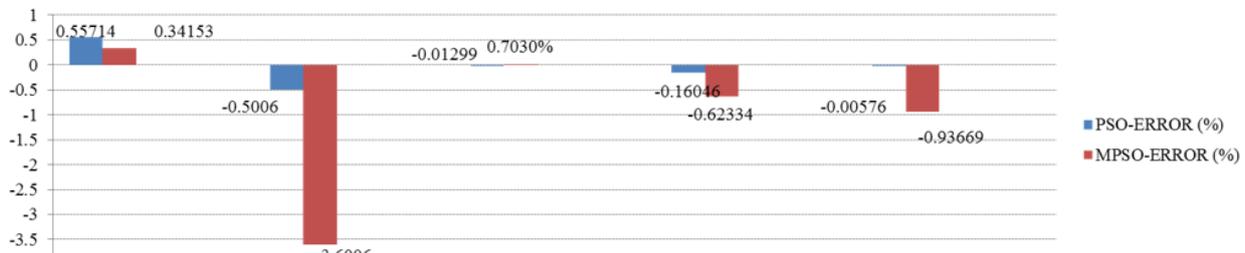
Figure 3.10: Bad Bearing Simulation Results using PSO



Then the simulation results are compared on error optimization. The results are compared in the below table percentage basis to suggest the better techniques of 3.4 with graphical representation 3.12:

Table 3.4: Error Percentage using MPSO and PSO for bad bearing fault for k=1

| Optimization | Armature circuit resistance [Ohm] | Armature circuit inductance | Moment of inertia [kg*m ²] | Flux | Viscous damping coefficient [Nm/rad/sec] |
|--------------|-----------------------------------|-----------------------------|--|-----------|--|
| PSO | 0.55714% | -0.5006% | -0.01299% | -0.16046% | -0.00576% |
| MPSO | 0.34153% | -3.6006% | 0.7030% | -0.62334% | -0.93669% |



The final results comparison will be performed in the end after acquiring the outputs of entire faults. However, it is obvious from the results of simulation that the particle swarm optimization technique optimizes the result rapid with less error percentage in bad bearing fault case.

b. Experiment and Simulation of Air Gap Eccentricity:

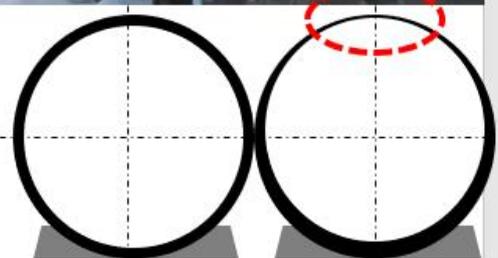
i. Eccentricity of Air Gap:

The eccentricity of air gap is inherited dynamic and static eccentricity which produces speed pulsation, ripple torque, stress and acoustic noise between the rotor and static part. For that reason it is essential for air gap eccentricity early detection. There are three main types of air gap eccentricity namely: 1) dynamic eccentricity; 2) static eccentricity; and 3) mixed eccentricity. The air gap spectrum impact will generate distinct spectrum and can be recognized during the examination. The air gap characteristic frequency equation is represented as follows:

$$f_{ag} = \frac{\{(k_{rt}R \pm k_d)(1 - s) \pm k_{ws}\}f_s}{p}$$

Where k_r is any integer between 0, 1, 2, 3,.....
 f_{ag} is the component of frequency due to eccentricity of air gap
 k_d is the order number of eccentricity with $k_d = 0$ as static eccentricity and $k_d = 1, 2, 3, \dots$ as dynamic eccentricity
 p is the number of poles that is half the number of poles = $P/2s$ is the ratio of slip k_{ws} is the stator MMF time harmonic order number f_s is the frequency of supply
 A static air gap eccentricity is established in the induction motor by machining the rotor and motor housing and then a grub screw is inserted in housing to transform the rotor symmetry. The below figures 3.14 (a) and 3.14 (b) indicates the method of eccentricity. An offset of 0.1 millimeter is made in a total of 0.4-millimeter air gap. Thus, 25 percent static eccentricity is acquired in this set up.

Figure 3.13: Rotor and housing of motor to acquire eccentricity



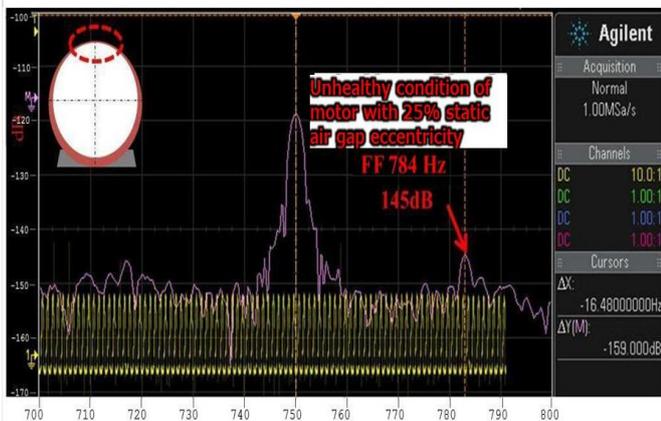
The expected frequencies of fault are denoted in the below table 3.4:

Table 3.4: Static expected frequency of 25% eccentricity of air gap fault condition

| Condition of Load | Speed | Slip | Kws =±1 | |
|-------------------|-------|------|-----------|-----------|
| No Load | 1395 | 0.07 | 787 hertz | 887 hertz |

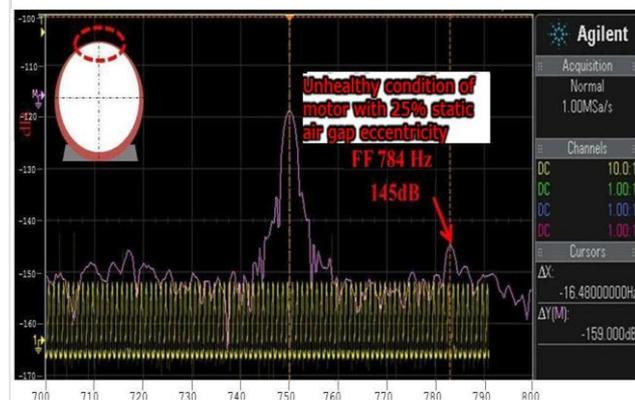
The SEW-EuroDrive Motor results are shown in the below 3.14:

Figure 3.14: SEW-Euro Drive Motor Spectrum in Healthy Condition at no load



The results of a SEW-Euro Drive Motor are depicted in the below figure:

Figure 3.15: SEW-Euro Drive Motor Spectrum in unhealthy condition at no load with kws =1



The signal with yellow color indicates the time domain signal and signal with white color indicates the frequency domain signal of the healthy induction motor. The center frequency is considered as $f=50$ hertz and the bands with slip side are less visible in healthy motor case. The result of static air gap eccentricity fault is shown in the below figure where the resultant frequency of fault is at 784 hertz with 145 decibel amplitude:

3.2.2 Optimization and Simulation:

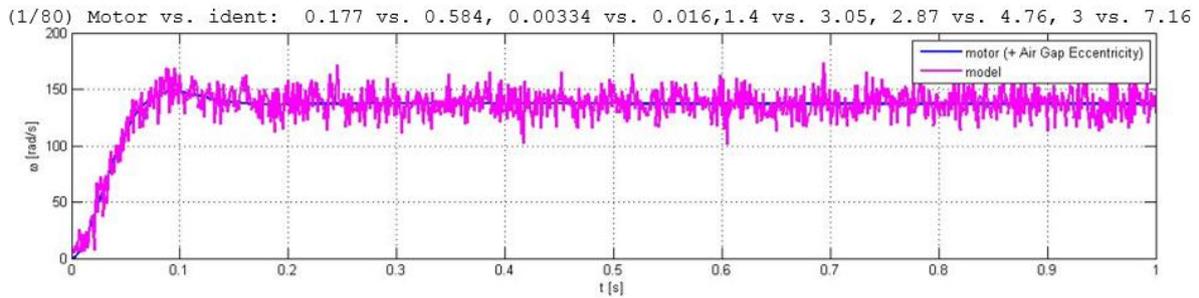
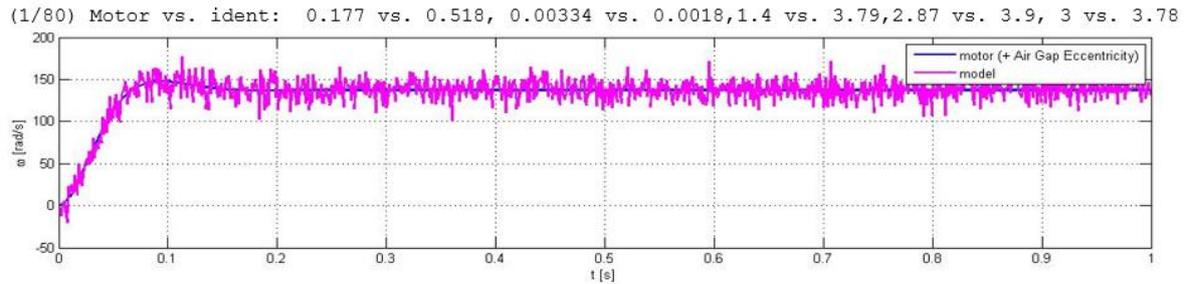
Now Modified Particle Swarm Optimization and Particle Swarm Optimization are employed for approximation of parameter that is to optimize the condition back to healthy one and for comparative research. The experiments are finished on 440V, kw, SEW Euro Drive induction motor and assessment of parameter is completed through SIMULINK/MATLAB algorithms. For the purpose of simulation, the similar set up of hardware has been employed and then the frequencies of fault associated to

25% static fault of air gap eccentricity with USB=887 hertz and LSB=787 hertz are considered as range of reference to optimize the induction motor faulty behavior. Applying the MPSO and PSO on the following parameters of motor and later the results are combined through SIMULINK/MATLAB:

| Parameters of Test motor |
|--|
| Ua = Rated Armature Voltage [V], 420 Voltage |
| Mm = Rated Torque [Nm], 20 nanometer |
| I = Rated Current[A], 3 Ampere |
| Ra = Resistance of Armature Circuit [Ohm], 0.177 ohm |
| La = Inductance of Armature Circuit [H], 0.00334H |
| N = Rated Speed [RPM], 1395 |
| $W = N * \pi/30$; Rated Speed [radius/second] |
| Jz = 1.4; Inertia Moment [kg * m * 2] |
| Psi = (Ua – Ra * I)/W; Flux |
| Ct = 3; Coefficient of Viscous Damping [Nanometer/radius/second] |
| USB = 887 hertz |
| LSB = 787 hertz |

Now with the Modified Particle Swarm Optimization and Particle Swarm Optimization the simulation is performed and air gap eccentricity is simulated. The below figure 3.17 shows the faulty condition behavior in Particle Swarm Optimization and Modified Particle Swarm Optimization:

Figure 3.16: Simulation of PSO for a SEW EuroDrive Motor in Unhealthy condition at no load with 25% eccentricity of air gap



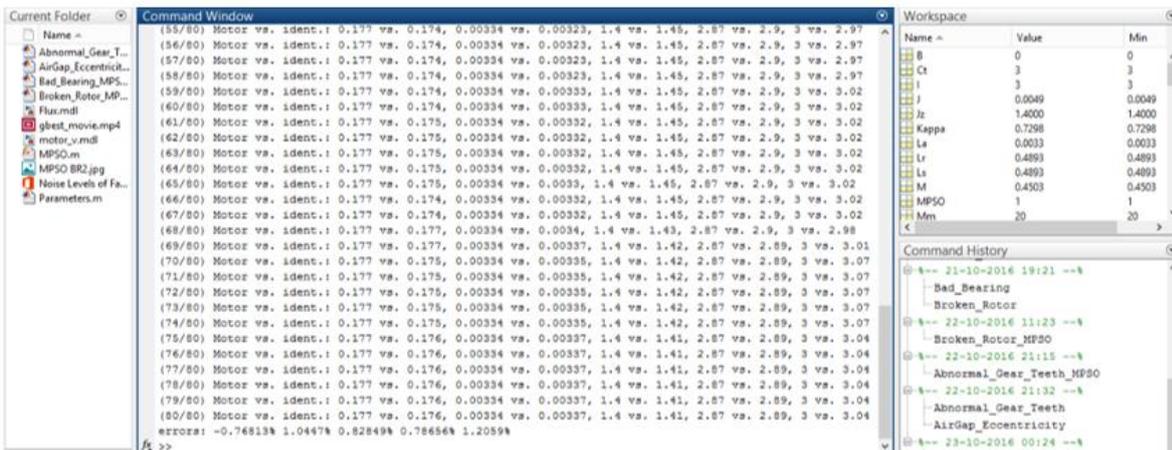
The below figures show the parameter convergence till 80 iterations. The figure 3.8 shows the error convergence using PSO:

Figure 3.18: Error convergence using PSO



Another figure shows the error convergence using MPSO:

Figure 3.19 Error convergence using MPSO

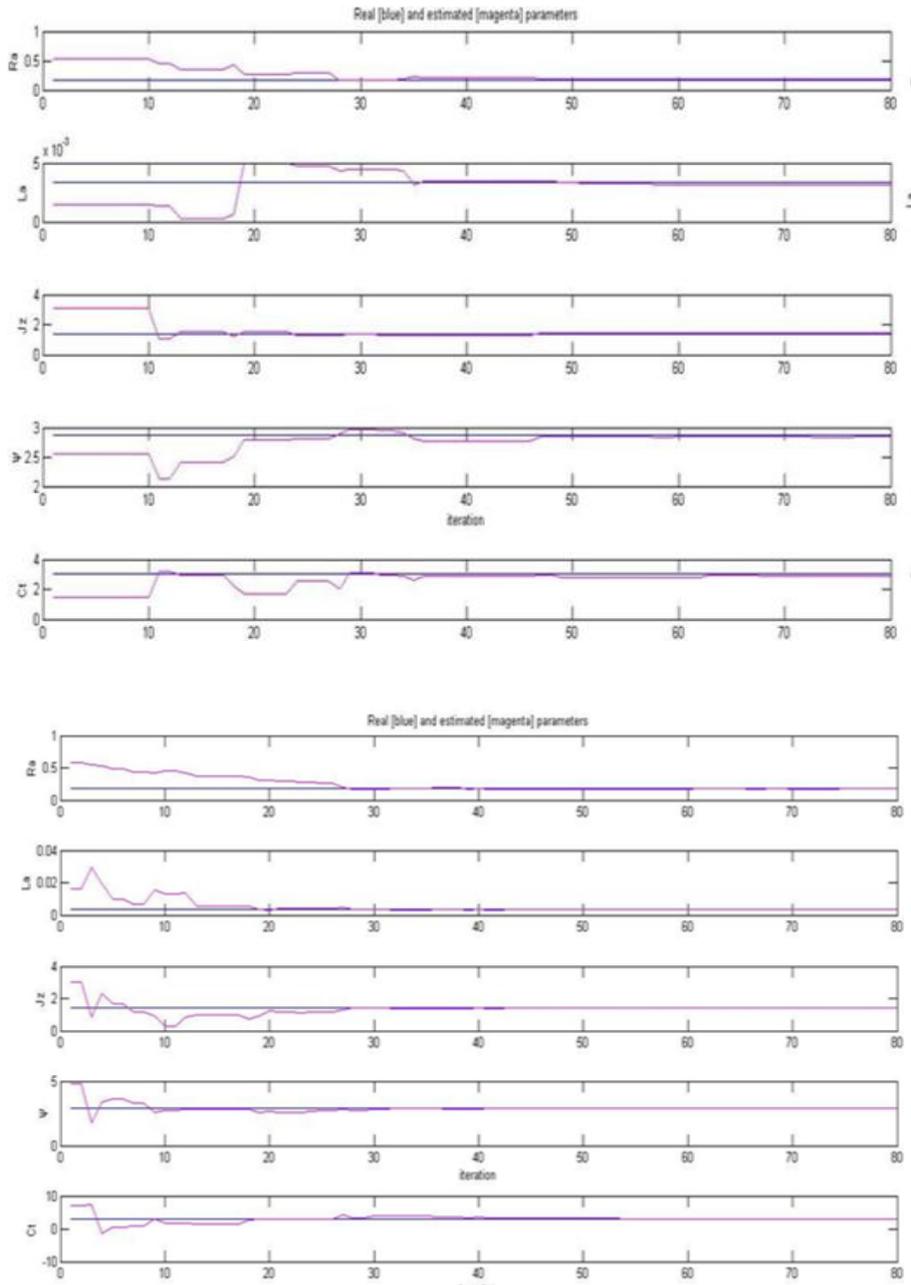


3.2.3 Results of Bad Bearing Fault:

The comparative research between the results of PSO and MPSO is carried out to verify the proposed method

effectiveness. The below figures shows the results of all parameter optimization using MPSO and PSO respectively

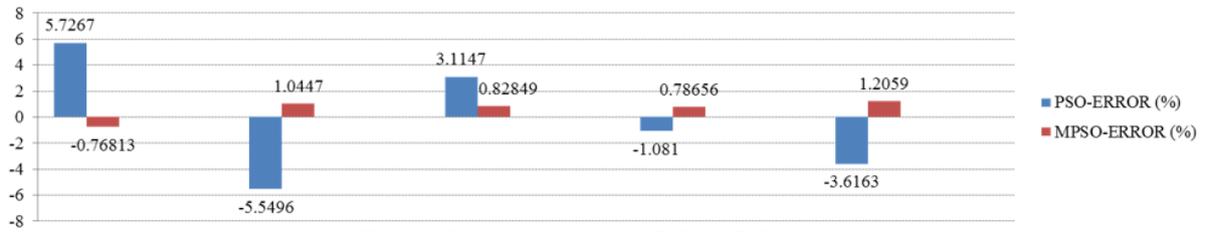
Figure 3.20: Air Gap Eccentricity Simulation Results using PSO



Then the simulation results are compared on error optimization. The results are compared in the below table percentage basis to suggest the better techniques of 3.4 with graphical representation 3.12:

Table 3.5: Error Percentage using MPSO and PSO for bad bearing fault for k=1

| Percentage of error | | | | | |
|---------------------|-----------------------------------|-----------------------------|--|----------|--|
| Optimization | Armature circuit resistance [Ohm] | Armature circuit inductance | Moment of inertia [kg*m ²] | Flux | Viscous damping coefficient [Nm/rad/sec] |
| PSO | 5.7267% | -5.5496% | 3.1147% | -1.081% | -3.3163% |
| MPSO | -0.76813% | 1.0447% | 0.82849% | 0.78656% | 1.2059% |



The final results comparison will be performed in the end after acquiring the outputs of entire faults. However, it is obvious from the results of simulation that the modified particle swarm optimization technique optimizes three parameters rapidly with reduced error percentage in case of 25% eccentricity of air gap in entire estimation of parameter.

After the entire hardware experiments completion and simulation of software the analysis and summarization of the bad bearing fault and air gap eccentricity results are performed on error percentage basis and value of fitness function:

c. Bad Bearing Fault:

The below table shows the results summary of bad bearing fault:

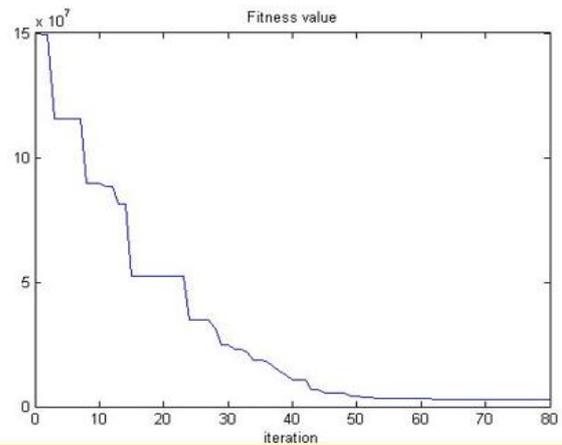
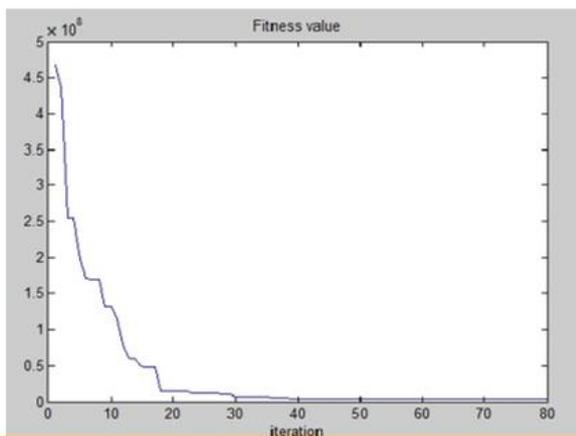
Comparison of Results:

Table 3.6: Results Summary of Bad Bearing Fault

| Fault frequencies | Optimization | Armature circuit resistance [Ohm] | Armature circuit inductance | Moment of inertia [kg*m ²] | Flux | Viscous damping coefficient [Nm/rad/sec] |
|-------------------|--------------|-----------------------------------|-----------------------------|--|-----------|--|
| LSB = 61.6Hz | PSO | 0.55714% | -0.5006% | -0.01299% | -0.16046% | -0.00576% |
| USB = 161.6Hz | MPSO | 0.34153% | -3.6006% | 0.7030% | -0.62334% | -0.93669% |

The below figure shows the comparison of the results of bad bearing fault:

Figure 3.21: Comparison of the results of Bad Bearing Fault



Inference:

From the above analysis it is inferred that Particle Swarm Optimization (PSO) is good optimization for bad bearing fault.

d. Air Gap Eccentricity:

The below table shows the results summary of Air Gap Eccentricity:

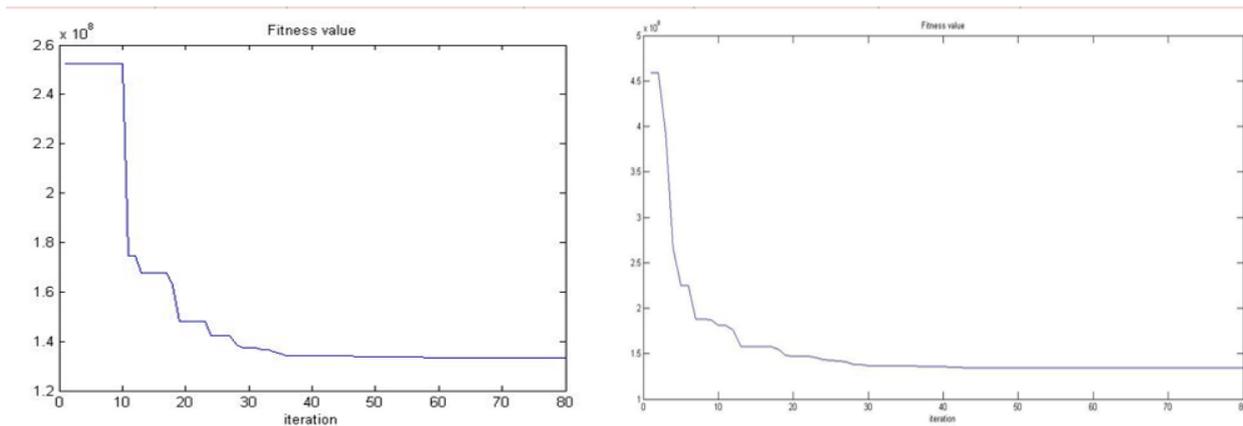
Table 3.7: Results Summary of Air Gap Eccentricity

Summary of results

| Fault frequencies | Optimization | Armature circuit resistance [Ohm] | Armature circuit inductance | Moment of inertia [kg*m ²] | Flux | Viscous damping coefficient [Nm/rad/sec] |
|-------------------|--------------|-----------------------------------|-----------------------------|--|----------|--|
| LSB = 787Hz | PSO | 5.7267% | -5.5496% | 3.1147% | -1.081% | -3.3163% |
| USB = 887Hz | MPSO | -0.76813% | 1.0447% | 0.82849% | 0.78656% | 1.2059% |

The below figure shows the comparison of the results of air gap eccentricity:

Figure 3.22: Comparison of the results of Air Gap Eccentricity



Inference:

From the above analysis it is inferred that Modified Particle Swarm Optimization (MPSO) is good optimization for bad bearing fault.

IV. CONCLUSION AND FUTURE SCOPE

Over the last decade, research has increased in a strong pace in the subject of fault detection and analysis in induction motors. In the present era, software is being presented with diagnostic characteristics to enhance strength and reliability in fault diagnostic methods. People participation in decision-making for fault identification is progressively being changed by Artificial Intelligence techniques. In this study a brief review of eccentricity fault is given in addition to their causes and impacts on the physical condition of induction motors. A number of indices used to find out eccentricity are being inducted together with their boundary circumstances and their further scope of research. Electric motors particularly induction motor has a significant role in the reliable and effective running of industries and procedures as a result of the low cost, intensity and financial maintenance. Initial identification of defects in the motors will contribute to prevent steep failures. The induction machine is considered as the single most conventional electromechanical energy exchange device accessible. Bearing failure is generally progressive but eventually its consequence upon the motor is disastrous. Eccentricity is described as unbalanced air-gap amid the rotor and stator of induction motors. As the findings suggest, the most important issues facing the usage of ANN are the range of the best inputs and exactly how to select the ANN parameters making the system compressed, and generating increasingly accurate network systems.

In general, induction motors are exposed to different stresses in operating conditions resulting in certain modes of defects. Therefore, condition monitoring considered essential also as to prevent catastrophic failures. A number of fault monitoring methods for induction motors could be classified as neural network, MCSA, signal processing techniques, and parameter estimation algorithm, artificial intelligence, which is also deeply explored in the current study. Here the main defects in induction motor and various fault detection techniques are presented. An effort has also made to assess and compare both internal and external defect non-invasive detection methods assuming recently used Artificial

Intelligence based, residual intelligence and signal processing based methods. Condition monitoring entails considering measurements on a machine so as to identify defects with an intention of lessening both unpredicted failures and maintenance costs. An effective condition-monitoring system is one that gives warning and forecasts the defects at initial phases. Monitoring system includes information regarding the mechanism in the form of primary data and by means of the usage of contemporary signal processing techniques; it is feasible to give fundamental analytical information to equipment operators before it crashes. The issue with this technique is that the results demand stable human interpretation. The consistent development of the condition-monitoring tools is the mechanization of the diagnostic method. To automate the diagnostic method, many fault detection techniques including artificial intelligence, fuzzy logic, and wavelet transform, neural network, etc. have been proposed.

In recent times, various research attempts have been performed to diagnose induction motor air-gap eccentricity fault employing stator and dynamic current signals as a result of their minimal cost and ease of application. As industry largely relies on the consistent and safe function of induction motor, fault diagnosis will contribute to inhibit the consequent failure of machine. Bearing faults are the major faults in induction machine, based on the size and category of the machine and it is also considered as an essential part in the machines exposed to lot of corrosion. The overall quality of bearing will disintegrate over a certain period of time, intensifying the resistance of the machine that might result in torque and speed oscillation. As a result of corrosion it might be exposed to fatigue bring in deterioration, if the stresses extend. As the current study suggested, in recent period, as a result of the significance of induction motors in industrial plants, parameter identification in terms of induction motor has developed as one of the most remarkable fields for scholars. Analyses in this subject are categorized in two types, which include on-line and off-line estimation. In terms of on-line approaches, a number of parameters are assessed whilst the motor is functioning in real time. These techniques largely find motor parameters by presuming a number of parameters to be known.

The most important issue in off-line assessment is that the parameters are defined separately employing off-line experimentations and some model might not be precise when employed in an online process. This study establishes a new method and put forward that to diagnose faults on the basis of multi-objective optimization (MOO) and also accentuated that when many problems cannot be handled as a single objective problem, the demand of MOO will emerge in order to optimize the defective condition. In this method the residual can be created through an observer. In order to lessen false alarm rates in fault analysis, many performance indices are developed into the observer design. A number of performance indices are put across the frequency domain to consist of the frequency distributions of defects, noise and modeling uncertainties. The future study should include various prevention techniques in use of induction motors and health monitoring of induction motors by signal processing can be explored further. Also, comparison of different techniques can be carried out in order to identify the appropriate technique for early fault detection of induction motors and other engineering products. Future studies can present the hybrid condition monitoring method for assessment of the mechanical faults (such as bearing faults and eccentricity) of the induction motor. The proposed techniques in the study impart the prospective for not only identifying the faults at a very advanced stage but as well the review of the motor condition and austerity of faults.

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