A New Artificial Neural Network-Based Failure Determination System for Electric Motors

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Abstract
In this study, a new measurement system was developed to determine failures and to define the level of failure that may occur in bearings and rotor bearings or in foot of motor in single phase capacitor start motor. In the system, the vibratory operation of the motor is provided by connecting different screws on the motor’s rotor mounted flywheel or by gradually removing the nut bolts of motor foot. The VB3 vibration sensor outputs were recorded to the computer with LabVIEW program at 1 ms intervals for one minute. The changing characteristics of sensor output for each experiment had more than one frequency component; therefore, Fast Fourier Transform (FFT) was performed for determining such components. When the obtained FFT graphs were analyzed, it was determined that the vibrations had harmonics of 50 Hz and its multiples; and it was observed that the frequency and amplitude values of first 5 harmonics could be used for determining the presence, type and level of failure but there was a nonlinear relation between each other. Therefore, 2 different artificial neural networks (ANN) customized separately were developed for determining the type and rate of the failure of motor. 80%, 10% and 10% of available data were reserved for training, testing and verification, respectively, and the ANN was trained. Accuracy degree for the ANN in the estimations following the training stage was calculated as $R = 0.97$–$0.98$. Furthermore, the results of ANN were compared with the results obtained using Sequential Minimal Optimization, Naive Bayes (NB) and J48 algorithms; and it was determined that the accuracy degree of ANN was higher. After this, a program was developed in MATLAB in order to work 2 ANNs with highest success together. Lastly, a system consisting of Raspberry Pi and a 7″ LCD screen, similar to the multimedia system in cars, was created to use at industrial applications.

Keywords Single phase capacitor start motor · Vibration sensor · Artificial neural network · LabVIEW

1 Introduction
Single phase capacitor start motors are used actively in refrigerant compressors, ventilators, aspirators, hand tools such as small grinding wheel and small machines. Although they have less failures compared to other electric machines, failures that occur in such motors may cause loss of manpower and time as well as downtimes in production processes of plants, increase in maintenance costs, and therefore, economical losses [1]. The result of study performed using 7500 motors on the failure types that occur in asynchronous motors by Institute of Electrical and Electronic Engineers (IEEE), and Energy Power Researches Institute (EPRI) is seen in Fig. 1 [2].

As seen in Fig. 1, approximately 47–52% of failure that occur in asynchronous motors are bearing and rotor failures. Such failures cause the engine to knock or the connection screws of the engine to loosen/break. This reduces the efficiency of motor or in other words, the energy consumed is increased. Considering that about 35% of the total electric power consumption in developed and developing countries is spent on asynchronous motors in houses or industry, the studies performed for the determination of failures in asynchronous motors and preventive actions for such failures are of great importance [1, 3].
There are studies in literature to determine the motor failure through motor currents and vibration sensor connected to the motor [4–12]. Mostly the examinations were performed on frequency domain in these studies [12–15]. Some studies used the fuzzy logic [16, 17] and ANNs to determine the presence of failure [18–24]. Also, artificial neural networks were used for determining the presence and type of failures in the internal mechanism of motor [25]. Such studies in literature are only for determining and monitoring internal mechanism (rotor and bearing) failures in motors [26–38]. However, motor foot failures (Fig. 9c) also become a problem in addition to internal motor mechanism failures in practical applications. Also the failure level of the motor can give information about the replacement or maintenance time of the motor. In addition to internal motor failures, a study in which foot failures and failure levels have been detected that has not been found in the literature. In this direction, a failure and level determination system has been developed in this study to determine the type and level of any failure in single phase capacitor start motors with the help of VB83 vibration sensors.

In the failure and level determination system, the vibration sensor voltages are transferred to computer using an electronic unit developed and a LabVIEW program. The voltage outputs of vibration sensors used in the study were examined based on the failure type and level. Firstly, FFT (Fast Fourier Transform) was performed in order to determine all frequency components forming the sensor data and then the harmonic components are closely examined to determine the type of failure. When frequency and amplitude values of harmonics determined for motor failure type and level were examined, it was found that there was a nonlinear relationship between both frequencies and amplitudes. In order to determine this nonlinear relationship, two ANNs have been developed. First artificial neural network determines whether there is any failure in the motor, and the second one determines the level of failure if there is rotor or bearing failure in the motor. Then, the ANNs were combined in a software developed in MATLAB. An online failure and level determination system was developed. In this way, the success of the online failure and level determination system developed are described in detail in the following sections.

2 Developed System for Failure and Failure Level Determination

The block structure of failure and level determination system for single phase capacitor start motors as developed in our study is provided in Fig. 2.

As seen in Fig. 2, VB83 vibration sensors were used in the system. Output voltages of sensors were amplified by the electronic unit and transferred to PC over NI USB 6210 DAQ card. NI 6210 DAQ card has 250 kS/s sample rate in 16-bit resolution. Thus, it has been possible to transfer the voltage changes of 47.2 μV to PC. In addition to this, a...
LabVIEW-based software was developed in order to transfer and record the voltages to the PC. Furthermore, it is possible to check the speed of motor through the electronic unit of system. The photos of stator and rotor belonging to the single phase capacitor start motor in which the failure and failure level were determined in the study are shown in Fig. 3. Motor’s stator has 24 slots, and its rotor has 18 bars. Other technical data of the motor tested are given in Table 1.

Table 1 Technical data of the motor

| Parameter          | Value         |
|--------------------|---------------|
| Voltage            | 220 V         |
| Current            | 2.0 A         |
| Power              | 0.3 kW        |
| Cosφ               | 0.97          |
| Torque             | 1.01 Nm       |
| Speed              | 2850 rpm      |
| Start Capacitor    | 20 µF         |
| Run Capacitor      | 10 µF         |
| Ingress Protection | IP54          |
| Duty Type          | S1            |

Under normal working conditions, the voltage induced in rotor bars is below 10 V. Therefore, rotor bars are not insulated from rotor lamination (core). Rotor lamination is made of siliceous sheets of 0.5 mm with insulated surfaces as in stator. Rotor lamination creates the magnetic path of flux passing from stator to air gap. Lamination carries the rotor windings and transfers the torque induced from magnetic path to the shaft. Short circuit bars were designed angled in order to reduce the vibration torques to occur in the motor shaft.

Two VB83 vibration sensors used in the study are located on the motor as seen in Fig. 4 on the basis of applications in literature [39–41].

Front panel of LabVIEW-based program developed in the study and the block diagram showing data acquisition settings of DAQ card can be seen in Fig. 5. While reading the processed sensor voltage on DAQ assistant interface, DAQ terminal should be selected checking whether the reference voltage is 0 V (GND).

3 Experiments Details

In our study, it was considered to place screws of different geometries at the shaft, respectively, to represent any damages that may occur in the bearings and rotor bearings of single phase capacitor start motor. For this, a flywheel was made from cast polyamide assembled on the rotor; and 2 screw holes of 3 cm were drilled on the same to input the screws. It was considered that the bearing damages would vibrate the motor less than the damages in rotor and therefore, that the small screws placed on the flywheel would represent such a damage (Fig. 6a, b). Reducing the quantity of part inside the flywheel would mean increasing the size of same kind of damage because the vibration would be reduced as the screw enters the flywheel. Furthermore, it was considered that removing the nut bolts of motor foot, respectively, would represent the damages that may occur at
the connection points of motor to the chassis (foot damage) (Fig. 6c).

As seen in Fig. 7, the length of screw placed in the fly-wheel is 3 cm (socket head cap screw) and 2.5 cm (set screw), respectively. The screw of 3 cm was defined as “1st Screw”, and the screw of 2.5 cm was defined as “2nd Screw”.

In our study, the screws were first placed one by one and then in pairs in 35 different positions; and the vibration signals created for each position were acquired using VB83 vibration sensors in intervals of 1 ms for one minute. In the next stage, screws inside the flywheel were removed; and four nut bolts connecting the motor to the chassis were removed firstly one by one and then in pairs in 10 different ways; and the data obtained from vibration sensors in intervals of 1 ms were recorded. It was determined in 45 different experiments that the voltage changes identified with the VB83 vibration sensors were different compared to the voltage obtained in the absence of screws causing the vibration in flywheel and that they were sufficient for determining the damage. Also the list of experiments and related photos are provided in “Appendix-A”.

4 Data Processing

Graphs of the sensor voltages that recorded for 45 different cases are drawn after completing the experiments. It was determined that the characteristics of the graphs drawn for both sensors were the same, only the amplitude values and phase frequency shifts were different. Therefore, upper sensor data with high amplitude values were used in the failure determination process. In Fig. 8a, b, c, the graphs of experiments coded as without failure, with rotor or bearing failure, and with foot failure are presented as examples. As seen in Fig. 8a, b, c, the data contain more than one frequency components. FFT (Fast Fourier Transform) was performed.
in order to determine all frequency components forming the data, and the results obtained for such examples elected as representatives are presented in Fig. 8d, e, f.

As seen in Fig. 8d, e, f, it was observed that the vibrations consisted of harmonics of 50 and multiples (0 to 1000). This is because the driving frequency of motor is 50 Hz. Although it was possible to determine the sensor voltages in frequencies of 50 and its multiples in view of Fig. 8d, e, f, it was observed that this was not sufficient to determine the failure type since the FFT graphics for 45 different experiments have the same characteristics. Whereupon, 0–0.4, 49.4–50.4, 99.4–100.4, 149.4–150.4 Hz harmonic fields of FFT graphs for the conditions of motor without failure, with rotor or bearing failure and with motor foot failure were examined closely. When the FFT graphs of fields shown in Fig. 9 are examined, it is observed that there are different harmonic components for each failure type around the frequency values selected. It was also determined that the frequency drifts of harmonics in frequencies beyond the selected frequencies are at the same order. However, they were not considered because of the small amplitude values of harmonics and in order to prevent calculation burden. The frequency and amplitude values of 5 harmonic components having the highest amplitude for 4 harmonic fields (0–2, 48–52, 98–102, 148–152 Hz) in FFT graphs of experiments with different failure types were used in the determination of failure type.

In addition to this, when we examine the FFT graphs of experiments with the same failure types but different failure levels closely, harmonic components with frequency and amplitude values different from each other are observed for the first 4 harmonic fields selected (Fig. 10). Frequency and amplitude values of 5 harmonic components having the highest amplitude in such harmonic fields were used in the determination of failure level. Meanings of “no failure”, “rotor or bearing failure 1”, “rotor or bearing failure 2”, “rotor or bearing failure 3” in Fig. 10a are “without any screw inside the flywheel”, “1st screw 3 cm inside the flywheel”, “1st screw 2 cm inside the flywheel” and “1st screw 1 cm inside the flywheel”, respectively. In Fig. 10b, meanings of “no failure”, “motor foot failure 1”, “motor foot failure 2”, “motor foot failure 3” are “all nut bolts not removed”, “right front nut bolt removed”, “left back nut bolt removed” and “left and right back nut bolt removed”, respectively.

When we examine the frequency and amplitude values of harmonics determined for the motor failure type and level, it is observed that there is a nonlinear relation between the frequencies and between the amplitudes. There are many algorithms to determine such nonlinear relation in the literature [5, 9, 16]. In this study, firstly ANNs were used as seen
frequently in the literature [18–24], seeking to increase the success of ANNs with various variations. Then, the success of ANN was compared to different algorithms such as SMO (Sequential Minimal Optimization), NB (Naive Bayes) and J48 as used frequently in the literature [7–9].

Multilayer perceptron (MLP) model among the ANN models was used to determine the nonlinear relations of both the frequencies and the amplitudes in this study. MLP networks have forward linkage and 3 layers in structure. Such layers are input, output and hidden layers. 2 different ANNs customized separately were used in this study to determine the type and level of motor failure. First ANN determines whether there is any failure in the motor and the second one determines the level of failure if there is rotor or bearing failure in the motor. Then, the ANNs were combined in a software developed in MATLAB, and an online failure detection system was developed. The flow chart of system and the properties of ANNs developed are provided in Fig. 11.

Fig. 9 Close examination of FFT graphs based on the failure type of each harmonic fields between a 0–0.4 Hz b 49.4–50.4 c 99.4–100.4 d 149.4–150.4

Fig. 10 Close examination of FFT graphs based on the failure level of one harmonic field (50 Hz) for a rotor or bearing failure b motor foot failure
Data Processing Results

In order to determine whether there is any failure in the motor and to determine its type if any, an ANN was developed with an input layer with 40 inputs, an intermediate (hidden) layer with 20 neurons, and an output layer with 3 outputs (1st ANN). Scaled Conjugate Gradient algorithm for learning and sigmoid transfer function for activation function were used in the ANN [42]. The amplitude and frequency values of highest 5 peak points obtained from 4 different harmonic fields (0–4, 48–52, 98–102, 148–152 Hz) were provided to this ANN as input; and the motor conditions corresponding to such values were provided as outputs. Then, 80%, 10% and 10% of available data were reserved for training, testing and verification, respectively, and the ANN was trained. Accuracy degree of trained 1st ANN was calculated as $R = 0.97846$ (Fig. 12).

If the failure in motor is a rotor or bearing failure, an ANN was developed, to determine the rate of failure, with an input layer with 40 inputs, an intermediate (hidden) layer with 20 neurons, and an output layer with 1 output with similar properties as the 1st ANN (2nd ANN). Bayesian regularization algorithm was used for training the ANN. The amplitude and frequency values of highest 5 peak points obtained from 4 different harmonic fields were provided to this ANN as input; and the motor failure conditions corresponding to such values were provided as outputs. Then, 80%, 10% and 10% of available data were reserved for training, testing and verification, respectively, and the ANN was trained. Accuracy degree for the 2nd ANN in the estimations following the training stage was calculated as $R = 0.98567$ (Fig. 13).

Following the determination of motor failure type and level with the same data using the ANN, studies were performed in order to determine the motor failure type using the SMO (Sequential Minimal Optimization), NB (Naive Bayes) and J48 algorithms, which are frequently used in the literature for classifications. Cross verification method was used as $k = 10$ but no success at or above the level of ANN was obtained. The results are presented in Table 2.
Lastly, a software was developed to use 2 ANNs with the highest success together in MATLAB program. The vibration measurements obtained in intervals of 1 ms for 1 min are provided to this software as inputs in the beginning (Fig. 14, Line:5). The program then first applies FFT in compliance with the system flow chart provided in Fig. 11; and determines the amplitude and frequency values consisting of highest 5 peak values in meaningful 4 frequency fields (Fig. 14, Line:7). Then, such values are presented to the 1st ANN as input to determine whether there is any failure in the motor and its type. If there is rotor or bearing failure in the motor, same amplitude and frequency values are applied to the 2nd ANN as input data, and the level of failure is calculated. Lastly, the program provides feedback with an output as in Fig. 15, and the program is closed after such notice. When input of 2nd ANN is experimental results of “1st_screw_0.5 cm_2nd_screw_0.5 cm_inside_the_flywheel”, the output is “Failure level 100%”. If the input of 2nd ANN is experimental results of “Without any screw inside the flywheel”, the output is “Failure level 0%”.

6 Conclusion and Discussion

This study created a new literature by determining the motor foot failures and their levels in addition to the rotor and bearing failures using the failure and level determination system. Developed system may be used widely in the industry in terms of determining the presence of failure in the motor in addition to its source and determining as to whether it is maintenance time for the motor. A system consisting of Raspberry Pi and a 7” LCD screen, similar to the multimedia system in cars, was created to use at industrial applications. The trained neural networks were run in Raspberry Pi, and the outputs obtained in the MATLAB were also obtained on Raspberry Pi (Fig. 16). Thus, it was confirmed that our system can be used actively in Controller Area Network (CAN bus) system of all motor vehicles.

Furthermore, this study may be used for online determination of maintenance periods of automobile engines. The approach defined as predictive maintenance in literature has different methods including Infrared Thermography (monitoring through thermal camera), Oil Analysis, Ultrasonic Monitoring, Motor Current Analysis, Steam Trap Analysis and Vibration Analysis. Most commonly used method is the vibration analysis as seen in Fig. 17 [43].

Joint application of failure determination system developed in the study together with one or several other methods

![Fig. 13 Result of 2nd ANN](image-url)

| Motor failure and type | ANN | SMO | NB | J48 |
|------------------------|-----|-----|----|-----|
|                        | 0.97| 0.79| 0.21| 0.89|
Fig. 14  Program and output for rotor or bearing failure and level
may increase the success of determination to 100%. Especially, this is important for the failure determination of asynchronous motors that are running alone and without a spare and that may affect production directly. The purpose of our next study is to increase failure determination success by using different methods together. In addition, if there are multiple faults in the motor (for example, rotor failure and shaft improper installation), the determination process of this situation can be a target for future studies.

Fig. 15 Output of motor foot failure

Fig. 16 Verification application with Raspberry Pi

Fig. 17 Rate of usage for predictive maintenance approach in the determination of failures
Appendix A

See Fig. 18 and Table 3

|   |   |   |
|---|---|---|
|   | (a) Experiment Number 1 | (b) Experiment Number 3 | (c) Experiment Number 7 |
|   | (d) Experiment Number 9 | (e) Experiment Number 11 | (f) Experiment Number 17 |
|   | (g) Experiment Number 19 | (h) Experiment Number 33 | (i) Experiment Number 35 |
|   | (k) Experiment Number 36 | (l) Experiment Number 37 | (m) Experiment Number 39 |
|   | (n) Experiment Number 40 | (p) Experiment Number 41 | (r) Experiment Number 45 |

Fig. 18 Photos of some experiments
Table 3: List of experiments

| Experiment number | Experiments | Experiment number | Experiments |
|-------------------|-------------|-------------------|-------------|
| 1                 | Without any screw inside the flywheel | 24 | 1st_screw_2 cm_2nd_screw_0.5 cm_inside_the_flywheel |
| 2                 | 1st_screw_0.5 cm_inside_the_flywheel | 25 | 1st_screw_2 cm_2nd_screw_1 cm_inside_the_flywheel |
| 3                 | 1st_screw_1 cm_inside_the_flywheel | 26 | 1st_screw_2 cm_2nd_screw_1.5 cm_inside_the_flywheel |
| 4                 | 1st_screw_1.5 cm_inside_the_flywheel | 27 | 1st_screw_2 cm_2nd_screw_2 cm_inside_the_flywheel |
| 5                 | 1st_screw_2 cm_inside_the_flywheel | 28 | 1st_screw_2.5 cm_2nd_screw_0.5 cm_inside_the_flywheel |
| 6                 | 1st_screw_2.5 cm_inside_the_flywheel | 29 | 1st_screw_2.5 cm_2nd_screw_1 cm_inside_the_flywheel |
| 7                 | 1st_screw_3 cm_inside_the_flywheel | 30 | 1st_screw_2.5 cm_2nd_screw_1.5 cm_inside_the_flywheel |
| 8                 | 2nd_screw_0.5 cm_inside_the_flywheel | 31 | 1st_screw_2.5 cm_2nd_screw_2 cm_inside_the_flywheel |
| 9                 | 2nd_screw_1 cm_inside_the_flywheel | 32 | 1st_screw_3 cm_2nd_screw_0.5 cm_inside_the_flywheel |
| 10                | 2nd_screw_1.5 cm_inside_the_flywheel | 33 | 1st_screw_3 cm_2nd_screw_1 cm_inside_the_flywheel |
| 11                | 2nd_screw_2 cm_inside_the_flywheel | 34 | 1st_screw_3 cm_2nd_screw_1.5 cm_inside_the_flywheel |
| 12                | 1st_screw_0.5 cm_2nd_screw_0.5 cm_inside_the_flywheel | 35 | 1st_screw_3 cm_2nd_screw_2 cm_inside_the_flywheel |
| 13                | 1st_screw_0.5 cm_2nd_screw_1 cm_inside_the_flywheel | 36 | Right_front_nut_bolt_removed |
| 14                | 1st_screw_0.5 cm_2nd_screw_1.5 cm_inside_the_flywheel | 37 | Right_back_nut_bolt_removed |
| 15                | 1st_screw_0.5 cm_2nd_screw_2 cm_inside_the_flywheel | 38 | Right_front_right_back_nut_bolt_removed |
| 16                | 1st_screw_1 cm_2nd_screw_0.5 cm_inside_the_flywheel | 39 | Left_front_nut_bolt_removed |
| 17                | 1st_screw_1 cm_2nd_screw_1 cm_inside_the_flywheel | 40 | Left_back_nut_bolt_removed |
| 18                | 1st_screw_1 cm_2nd_screw_1.5 cm_inside_the_flywheel | 41 | Left_back_right_back_nut_bolt_removed |
| 19                | 1st_screw_1 cm_2nd_screw_2 cm_inside_the_flywheel | 42 | Left_front_right_front_nut_bolt_removed |
| 20                | 1st_screw_1.5 cm_2nd_screw_0.5 cm_inside_the_flywheel | 43 | Left_front_right_back_nut_bolt_removed |
| 21                | 1st_screw_1.5 cm_2nd_screw_1 cm_inside_the_flywheel | 44 | Right_front_left_back_nut_bolt_removed |
| 22                | 1st_screw_1.5 cm_2nd_screw_1.5 cm_inside_the_flywheel | 45 | Left_front_left_back_nut_bolt_removed |
| 23                | 1st_screw_1.5 cm_2nd_screw_2 cm_inside_the_flywheel |  |  |

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