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# Android Based Robot for Industrial Application

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***Abstract* — Now a day's modernization and automation are carried out everywhere .Growing complexity and added functionality in automotive software has attracted more attackers. , it is now necessary to develop new architectures and design concepts that offer real tine interactive security system. Industrials works are made automated in various aspect. Like automated attendance temperature sensing switching lightning device on and off . One such communication methodology is done and monitored through mobile communication. In the previous system they use various cameras for continuous monitoring. It is highly vulnerable to software attacks and no provisions are taken for preventive measures attacks may not get identified, due to lack of supervision. The project involves automated robot for monitoring the machine parameter. Using keypad the robot moves its direction based on the instruction that identifies and monitor and enables the corresponding machinery. Once the machine is brought in to action, vital machine parameters are logged in to the PC. The parameter incudes machine's yoke temperature and load current. Based on the acquired parameters, the machine's healthiness is estimated. If there is a fault happens, the machine's fault information is sent to the concerned person through the wireless robot and the corresponding Machine ID is logged in to the fault log.**

## *Nomenclature*

| | |
|---|---|
| $i_{sa}, i_{sl}$ | Current Park's vector components, Voltage Park's vector components. |
| $m_a, mp$ | Mean values of $i_{sa}, i_s p$. |
| $id(f), Vd(f)$ | The fast Fourier transform of the positive sequence of the stator currents and voltages. |
| $P, Q, S$ | Active, reactive, and apparent powers. |
| $f$ | Power factor angle. |
| $fs$ | Electrical fundamental frequency. |
| $s$ | Slip. |
| $N_r$ | Number of rotor slots. |
| $p$ | Number of pole-pairs. |
| $N$ | Number of samples. |
| $n$ | Classes. |

## *Objective:*

- TO MONITOR THE MACHINE LIFE TIME IN INDUSTRIES.
- TO DIAGNOSIS THE FAULT TOLERANCE OF THE MACHINE.
- TO DESIGN A MOVABLE ROBOT VIA WIRELESS COMMUNICATION.
- TO TRANSMIT THE DATA VIA ANDROID MOBILE.

## **I.**INTRODUCTION

The THREE-PHASE squirrel-cage induction motors (IMs) are widely used in industry, particularly in high-tech domains due to their high power-to-weight ratio, low price, and easy maintenance. However, their performance includes constraints such as electrical and mechanical faults consequently a variety of condition-monitoring techniques have been developed to tackle these problems The methods of fault detection and diagnosis (FDD) can be classified into two major groups: the first group is the model-based method . This method uses a mathematical model to describe the normal operating condition of the IM. This model generates residuals that are zero when the IM under diagnosis is fault free and non-zero when particular faults are present in the IM. However, this method is based on a number of assumptions, which do not take into account the disturbances and the model uncertainties. Therefore, it is essential that the model takes these effects into account, which will allow a robust FDD. The second group is the signal-based method. This method is based on analysis of the measured signals. Suitable features of the measured signals are used to evaluate the operating conditions of the IM. These features are extracted by using: time-domain analysis, frequency-domain analysis or with more sophisticated techniques like time-frequency or wavelet analysis. However, the main drawback of this method is the need of data from the IM when affected by faults.

The proposed approach uses signal-based method rather than model-based method which can be difficult to design and even, in some cases, impossible to extract. This approach is based on the analysis of signals extracted from sensors (voltage, current, rotation speed, temperature, vibration, etc.) placed on the IM. However, some of these sensors are invasive and/or do not provide rich information about the IM. Therefore, it was decided to emphasize the analysis of electrical signals rather than the vibration or the acoustic analysis. Recent research reported that motor-current signature analysis (MCSA) is well known in condition monitoring of IM(s). However, when an IM is fed by a frequency converter composed by rectifier, dc link filter and a pulse width modulated inverter, electrical signals (currents, voltages etc.) become disturbed.

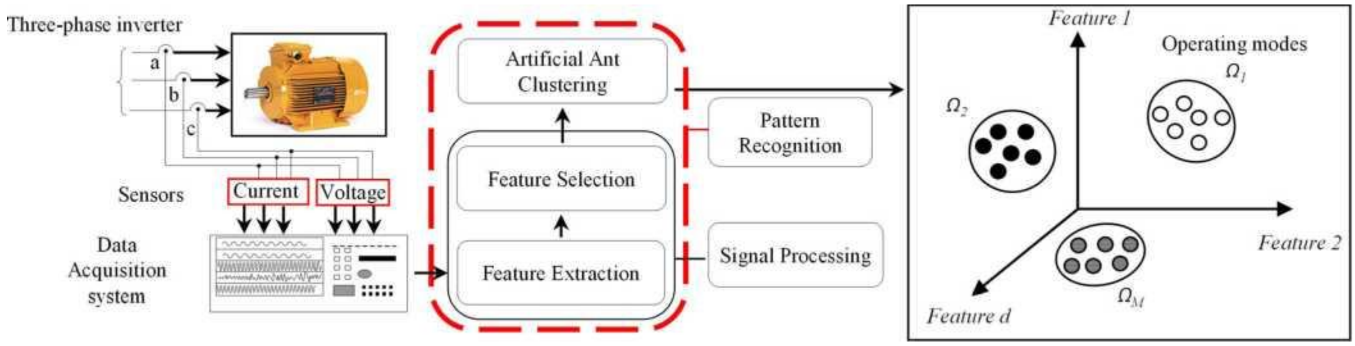



Fig. 1. Schematic representation of the (FDD) approach.

For this reason, it is necessary to use multiple signatures in order to reduce the effect of harmonic disturbance on the absorbed current. It was therefore decided to apply pattern recognition (PR) method combining MCSA and other features arising from transformations made on the current and the voltage signals with the aim of improving the monitoring. The proposed approach uses the artificial intelligence as an unsupervised classification technique for the detection and diagnosis of faults in IM(s).

The aim is to build a classifier such as hierarchical methods, *K*-means classifier, or neural networks which allows the identification of the operating modes. The performance of these methods depends on the prior knowledge about IM's operating modes. This knowledge is often imperfect; due to errors, electrical disturbances, and limited expert evaluations. This prior knowledge can also be incomplete because it lacks information about the operating modes of the IM, particularly the most dangerous ones. To avoid these drawbacks, we introduce a new intelligent optimization technique inspired from the behavior of ants in order to improve the detection and diagnosis of faults. Indeed, ants have become a powerful source of inspiration in the design of methods to solve optimization problems. The artificial ants systems (AAS) inspired by the behavior of real ants have been the subject of several studies in different application domains. The proposed approach has the ability to detect faults in the IM when the information about its operating modes is limited.

In such a context, this paper is structured as follows: An introduction to PR is done in Section III. The proposed FDD approach is done along two stages: signal processing and classification. In the first stage, a list of features sensitive to electrical and mechanical faults is extracted. Then, some of these features are filtered by a feature selection method in order to remove irrelevant and redundant features. In the second stage, we present in detail an unsupervised classifier based on the behavior of ants called the artificial ant clustering (AAC) technique. The sensitivity of the AAC is analyzed. In Section IV, we investigate the described approach using the AAC on an IM with bearing failure and broken bars. Final conclusions are drawn in Section V.

## II. EXISING SYSTEM

Wired monitored systems are successfully employed in many large industrial sites to monitor the critical devices and process parameters. Involves writing

overhead. Susceptible towards noise and electromagnetic interference. Higher data pay load due to raw data transmission. High level of uncertainty in diagnosis of results. Highly complex and expensive.

## III. ARCHITECTURE OF THE PROPOSED APPROACH

PR includes document classification, bioinformatics, data mining, speech recognition, and industrial automation. In the proposed system includes the following:

Movable robot, zigbee, android mobile, temperature sensor, and voltage sensor.

The approach described above can be applied to monitor the IM. In this case, the d-parameters of the feature vector result from measurements performed on the IM. A good knowledge of the system can help us to choose the most appropriate features. However, several measurements disturbed by noise can appear. Thus, the patterns $xi$, resulting from the same operation mode will not find a single point, but an area of points. If the features are well selected, each operating mode can be represented by a class in the multidimensional feature space as shown in Fig. 1.

The FDD approach is done in two stages: signal processing and data classification.

### *A. Signal Processing*

***1) Feature Extraction:*** In addition to analyze the stator current spectrum, we extract multiple features arising from transformations made on current and voltage signals. The researches carried out in show that the Park's vector approach can be used to detect faults in the squirrel-cage induction machines. Indeed, in experimental results show that it is possible to detect the presence of air gap static eccentricity in operating three-phase IM(s) using Park's vector. In the current Park's vector was successfully applied in the diagnosis of rotor faults, inter-turn stator faults, and mechanical load mis-alignment. In, the problem of bearing failure is diagnosed by the Park's vector approach. The authors also compared two FDD techniques, namely, the Park transform approach and the Concordia transform. Experimental tests were carried out on a 0.75 Kw two-pole IM with artificial bearing failure. Their results indicate that Park transform approach is more suitable than the Concordia transform.

Based on these researches, a list of features is extracted from voltage and current signals:

**Six features** are calculated from voltage and current Park's vector components.

- The standard deviation of $i_{sa}$ and $i_s p$ named $a_a$ and $ap$, respectively,

**|Np|**

- The peak-to-peak values of current Park's vector components $l_{sa}p = Isa + jIsp = Isa,pe^{je}$ named $S_a$ and $Sp$, respectively,
- The mean values $m_p$ and $m_q$ of the active and reactive powers (P and Q, espectively) normalized by the RMS value of apparent power modulus $S$ denoted $P'$ and Q', respectively,

**Twenty four features** are extracted from the spectrum analysis of the stator current.

- Amplitudes of harmonics around the supply frequency
- Amplitudes of harmonics around the principal slot harmonics
- Amplitudes of the fifth and seventh harmonics where $Np$ is the number of points in the signals. $ma, mp$ are the mean values of $i_{sa}, i_s p$, respectively. n $=1,2$. $k = 0,1$. $Y$ is the order of the stator time harmonics that are present in the power supply driving the motor $(7 = 1,2,3)$. $p$ is the number of pole-pairs and $s$ is called per unit slip.

**Two more features** are calculated from stator voltages and stator currents

- The power factor angle (y>) between the current and voltage.
- By considering the fast Fourier transform $i_d(f)$ and $v_d(f)$ of the positive sequence of the stator currents and voltages($i_d$ and $v_d$, respectively). The direct impedance $Z_d$ is the ratio between the fundamental components of $v_d$ and $i_d$.

***2) Feature Selection:*** Signal processing involves techniques for extracting features to build the multidimensional feature space, but some of these features are irrelevant and redundant.

This may affect the quality of detection and diagnosis. Thus, the selection of features is important to improve the monitoring. The main benefits of the feature selection are:

- removal of irrelevant, noisy, and misleading features for more compact representation;
- better understanding of essential characteristics of the underlying process;
- dimension reduction for less complex computation;
- Better classification results.

It has been reported in the literature that the sequential backward selection (SBS) and the genetic algorithm (GA) are two search methods commonly used in the feature subset selection problem. A comparative study between the SBS and the GAwas carried out in [48]. This study showed that both methods gave almost the same results for selecting the best features. It was therefore decided to apply the SBS because it requires less computation time. The aim is to seek among the full feature set, the best $d'$-features that maximize a criterion named $(C_q)$. This criterion takes into account the distance between the classes defined by the inter-class scatter matrix $S_B$ and the compactness of the classes defined by the intra-class scatter matrix $S_W$

where $M$ is the number of classes. $ni$ is the number of data in the class $Q_i$. $N$ is the total number of data. $g_i$ is the gravity center of the class $Q_i$. $x_i j$ is the jth data in the ith class $Q_i$, and g is the gravity center of the data set

*B. Data Classification*

Behind the term of classification, two categories can be distinguished: the supervised and unsupervised classification. In the unsupervised classification (also called clustering), we try to find groups (classes) which are the most compact and separated as possible from a data set representing some patterns. Then, we assign the new data to one of the found classes. Supervised classification, however, requires a supervised learning to build a discriminate function based on trained data. From this function, the new data are affected to one of the classes obtained by the trained data. The AAC belongs to the first category, it is an intelligent tool optimized by the AAS to classify and discover the new operating modes.

The AAS are heuristic techniques inspired by the behavior of ants and their ability to solve optimization problems. It has been shown that a colony of ants can use a chemical substance called "pheromone" to find the shortest way toward a source of food. Given the simplicity of the behavior of ants, computer scientists and engineers were able to transform this model to solve optimization problems. The AAS proposed in [49] has been applied to a combinatorial optimization problem called the Traveling Salesman Problem (TSP). The TSP seeks to minimize the cost of the way for a salesman to visit all the cities exactly once and return home. In spite of the fact that the TSP is a *NP*-hard problem, it can be solved easily by the AAS. By drawing inspiration from TSP, we can optimize the AAC.
The aim of the AAC is described as follows:

Given *N* patterns (data), each one described by a set of *dd*-features, one seeks a clustering of these data in *M* classes, $n_2 \ldots \& M$) so that similar data are grouped in the same classes while dissimilar data are in separated classes. The value of *M* is unknown. The clustering of these data is obtained by a succession of interactions between the ants. Each ant has behavioral rules which it follows according to the situations that it meets.

- The nest contains the data to be classified and corresponds to the starting point for the ants which leave toward the source of food.
- The path taken by the ants toward the source of food corresponds to a class, and the set of paths taken by the ants before they arrive to the source of food constitutes the final classes.
- The search for a path toward a source of food corresponds to the search of a class for the data carried by the ant. The choice of a class for this data means the choice of a path.
- Each ant memorizes the path taken by putting a quantity of pheromone to optimize the classification.
- The choice of a path which will be taken by the ant depends on the similarity between this ant and all the ants who have taken this path.

The tasks of the AAC can be summarized in four steps as shown in Fig. 2.

1) ***Step 1:*** Let us consider a population of N ants $Ant_{iie}(_{ly}\wedge\wedge_N)$ carrying N data. These ants (initially in the nest) attempt to classify these data in a first set of classes $(m < N)$ while trying to choose a path to the source of food. This is done by a similarity function $Sim_l(Ant_i, Antj)$; it measures the degree of resemblance between an ant in the nest ( Antj ) and another one in its path toward the source of food ( Anti)

Where $d(Xi, Xj)$ is the Euclidean distance between two ants. *(e, f)* G [0 — *1]* are two parameters that define the importance of the pheromones deposited by the ants and the distance between them. *A* is the *A*th ant that remains in the nest, and *Ti* is the quantity of the pheromone deposited by the ant *(Anti)* in its path when it leaves the nest.

Initially, the quantity of the pheromone deposited by each ant is

Once the nest is empty, the quantity of the pheromone deposited by ants on each path is updated by

Where £ is a constant related to the quantity of pheromones deposited by ants, and $nAnt_i$ is the number of ants on the *i*th path.

The role of the parameters *e* and *f* is the following: If $e = 0$, this corresponds to a classic similarity between two ants based on the Euclidean distance. Euclidean distance is the square root of the sum of squared differences between corresponding features of the two data carried by the ants. If $f = 0$, only the pheromone amplification is taken into account. This will allow a careful choice of the path on the basis of the quantity of pheromones deposited by the ants. Therefore, a tradeoff between the distance and the pheromones is a good approach to optimize the classification.

*2)* ***Step 2:*** Once the nest is empty, these ants continue their paths and attempt to optimize the classification of the data in a *second set of classes* $(m^f < m)$ while choosing a path to the source of food. This is done by another similarity function $Sim_2(Ants_i, Antsj)$; it measures the degree of resemblance between a group of ants $(Antsj)$ which is more distant than another group of ants $(Antsi)$ compared to the source of food

The quantity of the pheromone deposited on each path taken by ants is updated by

Where $a$ G $[0 — 1]$ is the evaporation factor; it is used to avoid an unlimited accumulation of the pheromones on the paths and $g_i, gj$ are the gravity centers of the data carried by the group of ants $Ants_i$, $Antsj$, respectively.

These ants attempt to classify the data while trying to maximize the inter-class scatter and to minimize the intra-class scatter. This is done by a criterion of quality called "$C_q$ "given.

*3 ) Step 3:* The final set of classes $n_{iiG}(j\ ,M)$ is obtained by the principal component analysis (PCA) [50] and the -means clustering [51]. The PCA extracts the important in- formation from the d'-features, to represent them as a set of new orthogonal features called principal components, and to obtain a better description of the classes by reducing the dimension(number of features) without losing too much information. The-means is a well-known technique in unsupervised learning. It is formulated by minimizing a formal objective function, mean-square-error distortion based on the Euclidian or the Mahalanobis distance. It is used to split the *second set of classes* into two subclasses in order to maximize the inter-class scatter and to minimize the intra-class scatter.

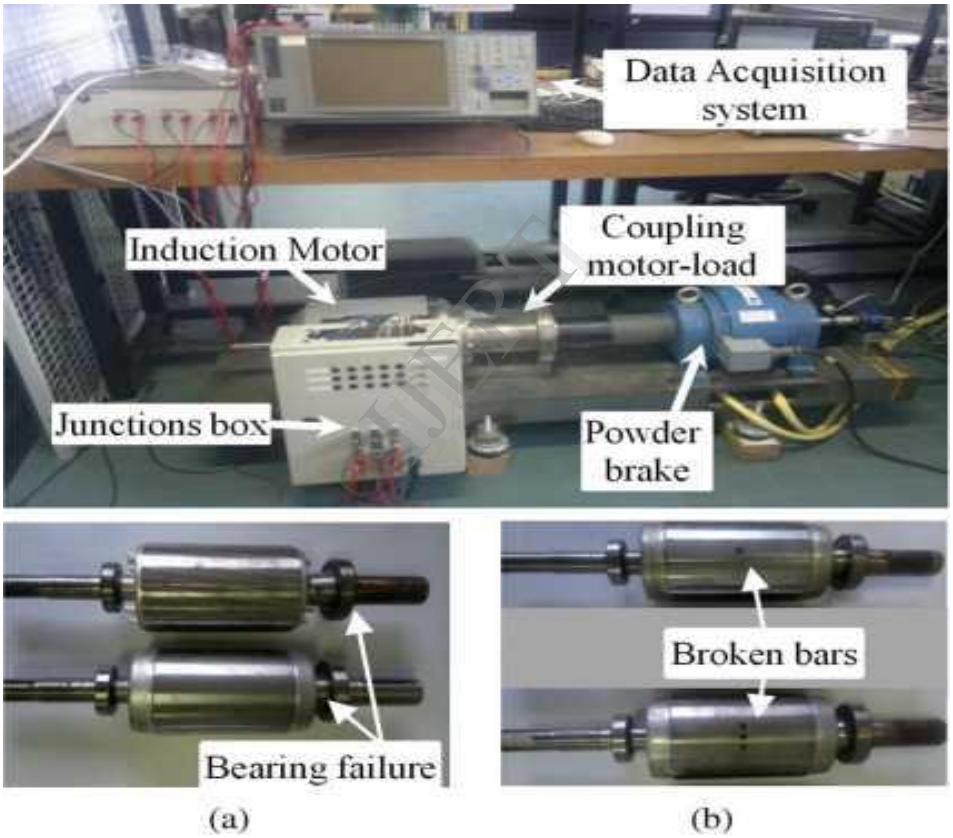


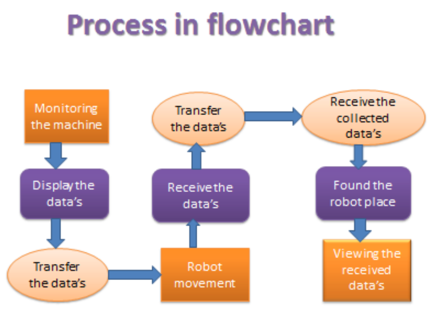

*Fig. 5. Experimental setup. (a) Bearing failure; (b) broken bars.*

Another criterion of quality called $C_{G(l,\ldots,M)}$ used in order to detect the new operating modes or to minimize the error of classification by rejecting the ambiguous data. Then, it is possible to apply a more attentive treatment to the rejected data in order to remove ambiguity*4 ) Step 4:* The final step is the decision rule; it assigns each new measure $x_{new}$ (new data) to one of the obtained classes by measuring the degree of resemblance between the new data and the obtained group of ants *(Antsi)*

Each new measure has a threshold of similarity allow-ing to define whether this measure is sufficiently or not.

These above methods are used for finding the fault of an induction motor by using artificial ant clustering techniques. Here voltage and current fault is only detected (or) diagnosed by parks vector approach method. The overall view of this method is used for finding the fault of an induction motor with artificial ants method but it is difficult for finding the fault.

## IV. PROPOSED METHOD PROCESS




The above flowchart shows that the function of android based robot for industrial application.

The base station which means machine is inter faced with voltage, current sensors these two sensors are generally used for finding the temperature and voltage level of a machine.

## V. CONCLUSION

A new approach to intelligent FDD of three phase IM using single based method has been proposed in this paper. Multiple features extracted from MCSA and transformations made on voltage and temperature sensors are used to derive rich faulty information to improve the monitoring. Here wireless movable robot is used for monitoring and it transmitting the information to the android mobile.

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