Probabilistic Neural Network Based Identification of External faults Experienced by 3-Phase Induction Motors

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Abstract

Fault diagnosis and condition assessment (FDCA) of rotating machines is critical due to the pivotal role that these machines play in our industries. Proper FDCA not only augments the machine's operative lifecycle, it also improves its efficiency, thus reducing chances of cataclysmic failure. This paper defines a realistic FDCA method for 3-phase induction motors using an open source dataset. External faults experienced by IM are monitored by the probabilistic neural network (PNN) whose performance characteristics are then compared with those of Multi-Layer Perceptron (MLP) revealing that the PNN algorithm is much quicker, thereby resulting in lessening of the workload experienced by a computer substantially. RMS value of 3-phase voltages and currents are utilized as input variable for model formation to identify the 6 types of external faults experienced by IMs' and normal operating (NF) condition. The developed system is then put to the test utilizing a sample set of 160 readings to highlight the efficiency and accuracy of the system for multiple fault scenarios.

Keywords: *Induction motor; fault idetification; MCSA; artificial intelligence; probabilistic neural network (PNN)*

1. Introduction

Electric motors are the lifeline for many important industrial applications such as power generation and manufacturing. They are widely used to drive the system in pumps, lifts, cranes, hoists, lifts, compressors, large capacity exhaust fans, driving lathe machines, crushers, in oil extracting mills, textile and paper mills, etc. Up to 90% of all electric motors used in industry and domestic appliances are either three-phase induction motors or single-phase induction motors [3].

Induction motors are the most widely used type owing to their simple construction, ruggedness, reliability and low cost [1-2]. This simplicity in construction is made possible by the fact that only the stator needs an active power supply as the rotor works due to electromagnetic induction. However, as is true for other machines, Induction motors are susceptible to breakdowns due to faults. It goes without saying that such situations lead to financial losses as well as wastage of time, which effect productivity in industries. Over the past several years, many conventional as well as artificial intelligence (AI) based fault recognition processes have been suggested for prevention of fatal errors in case of Induction motors. While conventional techniques were partially successful in this endeavor, it is the microcontroller based techniques using AI models which have proven to be the most effective due to their higher reliability and cost effectiveness [1-4].

Induction motor faults can be classified into several types [4]. Some of these categories are stator faults, rotor faults and bearing faults. Some of these faults have been summarized in Fig. 1. In this paper, we have confined our area of focus to the detection of external faults experienced by induction motor that can affect performance of IM. The external faults dealt with in this paper are single phasing (SP), unbalanced voltage (UB), under-voltage (UV), over-voltage (OV), locked rotor (LR) and overload (OL). Some of the early AI models have been applied in this field are based on the Artificial Neural Network (MLP) [1-2]. These models, however, have some drawbacks.

The MLP method involves determination of local minima and an optimal network structure, both of which are time intense processes. There's also a threat of over – fitting [5]. The PNN approach overcomes all of these drawbacks. In general, PNN achieves much more superior generalization performance at much quicker learning speed as compared to standard BP based MLP.

The paper has been written in the following manner : Section 1 introduces the topic as well as summarizes some of the early work done in this field. Section 2 gives a detailed description of the data set utilized as well as the methodology implemented. Section 3 gives an overview of the design process for the Fault Detection System (FDS). Sections 4 and 5 summarize the findings of the paper as well as discuss its future applications and modifications.

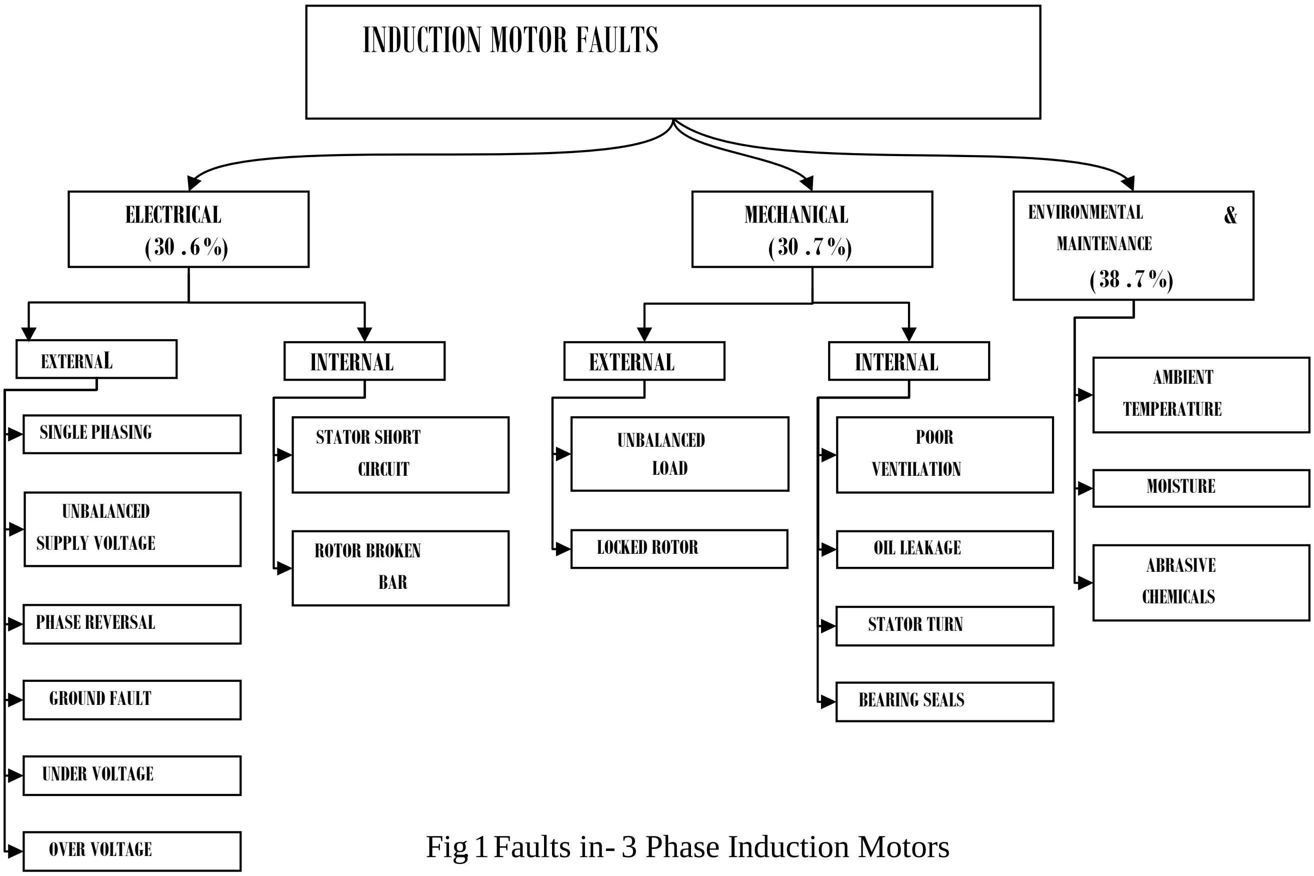

Fig 1 Faults in- 3 Phase Induction Motors

2. Material and Methodology

2.1 Database Used

A dataset consisting of 788 readings has been used for developing the PNN based external fault identification. These readings have been taken by simulating faults on a 1/3 HP Squirrel Cage induction motor. The external faults replicated are namely single phase, unbalanced, under voltage, over voltage, locked rotor and over load fault.

In reference [1-2] and [3], the SVM and MLP approach for identification of external faults have been mentioned. Our aim is to develop a PNN based model, thus developing a higher accuracy model as compared to the previously applied MLP algorithm.

2.2 The PNN Algorithm

The back propagation technique based Multi-Layer Perceptron (MLP) owe their effectiveness to their simultaneous scattered process & training proficiency. They also have a few inadequacies. For instance, the sluggish convergence impedes its adaptation capability. An additional difficulty faced is the determination of the optimal number of layers as well as hidden units [5]. All these features together make it a very attractive option.

The algorithm operates as a classifier that learns to classify data samples into either 2 (binary) or multiple (multi-class) categories. The numbers of input nodes as well as predictor variables are identical as are the number of hidden nodes and training samples, with 1 hidden node allocated to every training sample. The quantities of the output nodes of the PNN and the dependent variables whose values are being predicted are the same. A PNN consists of a quick training procedure thereby providing strong adaptableness, requiring a single-pass, thus doing away with any requirement for iterations to adjust weights for the network training.

The design of the PNN model has been described in Fig.1, which contains 3 layers: the input layer, hidden layer and output layer. The hidden layer consists of an activation function applied to the distance between the unknown input & the training sample. As an example, the input vector $\alpha = [\alpha_1, \alpha_2]$ is applied to input nodes χ_1 to χ_2. In the hidden layer, the network contains 5 nodes, γ_1 to γ_5, corresponding to five examples with weights attached to input nodes. Output weights are given 1 of 2 values – 1 represents a faulty condition whereas 2 signifies the opposite. Weights between hidden nodes & output node ϕ_1 are designed to allow ϕ_1 to compute the sum of all probabilities correspondent to the 1st category only from $\beta_1 = (\gamma_1+ \gamma_2)/ (\gamma_1+ \gamma_2+ \gamma_3+ \gamma_4+ \gamma_5)$, i.e. emulating the Bayesian confidence in decision making [5-6].

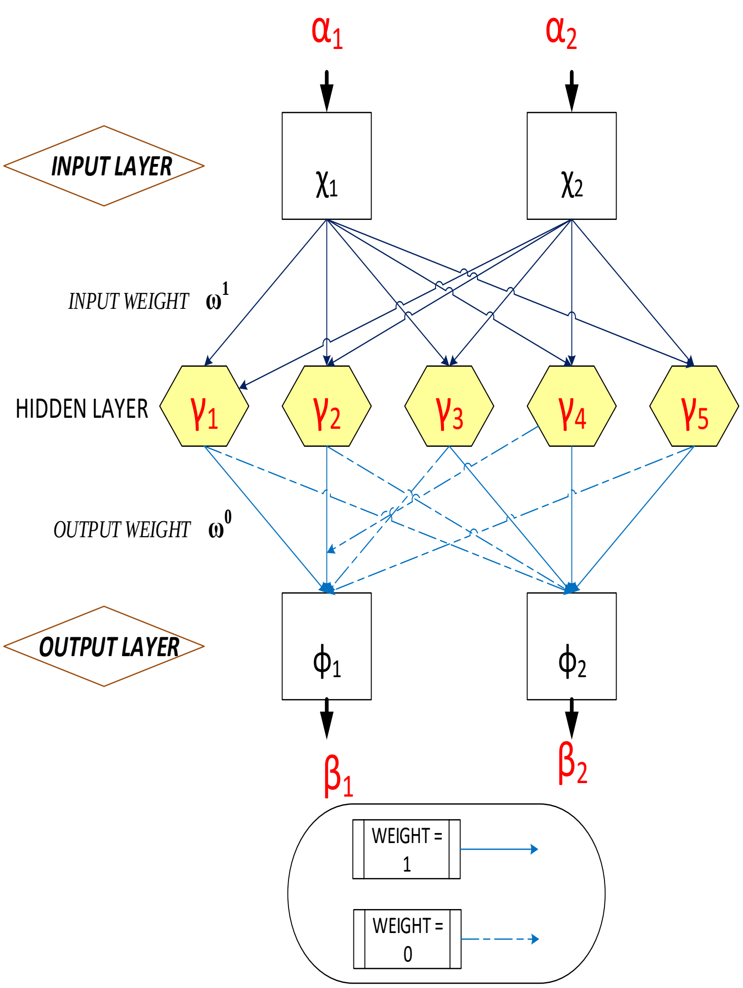

Fig. 2. PNN Architecture [5]

Now we extend the PNN design to n input nodes (χ_1 *to* χ_n), k hidden nodes & p output nodes (ϕ_1 *to* ϕ_p). The design process consists of 2 main steps: the learning stage & the recalling stage:

Stage 1: Generate input weight (ω^I) between input node (χ_i) & hidden node (γ_k) for every training sample (α_k) :

$$\omega^I_{ki} = \alpha_i(k) \qquad (1)$$

Where $i = 1,2,3,4,5,....n$ and $k = 1,2,3,4,5,....k$ the & input weight ω^I is the $k-by-n$ matrix = $[\omega^I_{ki}]_{kxn}$ training samples are

$$\alpha(\mathrm{k}) = [\alpha_1(\mathrm{k}), \alpha_2(\mathrm{k}), \alpha_3(k)........\alpha_\mathrm{i}(\mathrm{k}),....\alpha_\mathrm{n}(\mathrm{k})].$$

Stage 2: Generate output weight (ω^O) between hidden node (γ_k) and output node (φ_j) :

$$\omega^O_{kj} = \begin{cases} 1, k \in Category1 \\ 0, k \in Category2 \end{cases} \qquad (2)$$

Where the numbers 1 & 2 represent the category of the sample.

where j = 1, 2, 3, ..., p output weight ω^O is given by the $k-by-p$ matrix = $[\omega^O_{kj}]_{kxp}$ and the number of training samples by k, dimensions of χ by n & dimensions of β by m.

Stage 3: Applying the test vector (α_{test}) to the network.

$$\alpha_{\mathrm{test}} = [\alpha_1, \alpha_2.......\alpha_\mathrm{i},....\alpha_\mathrm{n}]$$

Stage 4: Calculate the probability of test vector (α_{test}) by means of the Gaussian activation function:

$$netk = \sum(\alpha_i - \omega^I_{ki})^2 \qquad (3)$$

$$\gamma_k = \exp(-\frac{net_k}{2\nu^2}) \qquad (4)$$

where ν is smoothing factors, $\nu_1= \nu_2= \nu_3=. . . . .= \nu_k= \nu$

The distance between the test vector and all the training samples is used for the Gaussian function.

Stage 5: Calculate the probability of ϕ_j as the sum of

$$\phi_j = \sum_{k=1}^{k} \omega_{kj}^{O} \gamma_k , \quad \text{for } k \in category1 \qquad (5)$$

Stage 6: Normalize the output probability by dividing the sum by γ_k. The output probability P_j is:

$$\Pr obP_j = \frac{\phi_j}{\sum_{k=1}^{k} \gamma_k} \qquad (6)$$

Stages 1 & 2 are categorized as the learning stage. Stages 3 to 6 are termed as the recalling stage. In the learning stage, the network creates the input weight (ω^I) and output weight (ω^O). The recalling stage is where it tests the data & computes the probability for the test vector.

3. External Fault Identification Using PNN

3.1 Training And Testing Data

The recorded dataset is divided into 2 categories – Training data (628 cases) and Testing data (160 cases). Each set of readings corresponds to one of the following conditions of an electric motor -NF (154 cases), single phase-SP (85 cases), unbalanced-UB (450 cases), under voltage-UV (49 cases), over voltage-OV (10 cases), locked rotor-LR (10 cases), and over load-OL (30 cases).

The PNN fault classifier works by using this dataset as input.

3.2 PNN Based External Fault Identification Model Formation

The classifier model used for fault classification in 3-phase induction motors is designed using 6 inputs: 3 phase rms currents and 3 corresponding rms voltages. PNN based fault identification model for induction motor is designed using the aforementioned 788 cases. These data samples, along with their matching target vectors, are stored in the PNN Data Base. The PNN is an architecture of three layers along with 6 inputs α_1 to α_6 (3 rms currents and 3 rms voltages), 7 outputs β_1 to β_7 (No fault ,Overload fault ,Unbalanced supply voltage, Locked rotor ,Single phasing ,Under voltage & Over voltage) and hidden nodes γ_1 to γ_{788} (i.e. being equal to number of training data samples).

A graphical representation for the result is obtained using MATLAB [6] is shown in Fig. 3. The 628 samples (training data set) for different external faults of three phase induction motor are shown using blue colored dots and the new sample is represented by using red colored dots.

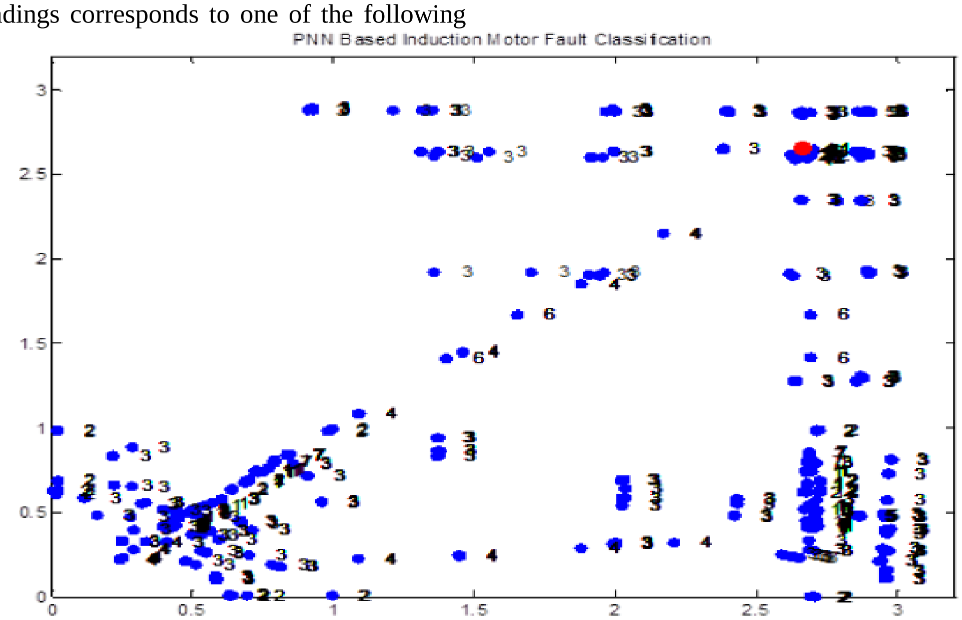

Fig. 3. PNN based induction motor external fault identification

The performance of the PNN model classifier is examined by:-

Model Prediction Accuracy (MPA),

$$MPA = \frac{Total\_Samples|_{accurately\_predicted}}{Total\_Samples|_{dataset}} \qquad (1)$$

Mean Squared Inaccuracy (MSI),

$$MSI = \frac{1}{n}\sum_{k=1}^{n}(E_k)^2;\ \text{Where}\ E_k = |RO_k - OO_k| \qquad (2)$$

Here n equals the number of samples in data set, RO_k is the required output & OO_k the obtained output.

The Root Mean Square Inaccuracy is calculated by determining the square root of the Mean Squared Inaccuracy.

The Mean Absolute Percentage Inaccuracy (MAPI) is given as:

$$MAPI = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{Fault_{PNN\_fault\_classifier} - Fault_{original}}{Fault_{original}}\right| \times 100 \qquad (3)$$

4. Results and discussions

The prediction accuracy is assessed using MAPI as specified by Amit Kumar Yadav [7]. The MAPI ≤ 10% indicates high identification accuracy, 10% ≤ *MAPI* ≤ 20% indicates good identification, 20% ≤ *MAPI* ≤ 50% indicates realistic identification, and *MAPI* ≥ 50% indicates erroneous predicting. With this, the maximum MAPI of the tested voltage and current samples for the PNN model is 0.20755%, indicating higher accuracy of 99.515% for external fault identification as shown in Table 3.

The results of the proposed model are compared with the results obtained using the MLP algorithm as shown. A selected set of samples has been used for comparing the performance of the 2 models. The output of the MLP model is given as a binary code. It is seen that PNN gives better results when compared with MLP. The tabulated results are as summarized in Table 2.

Table 1. The code for output player of MLP model

FAULT TYPE	NF	OL	LR	SP	UV	OV	UB
BINARY CODE	1000000	0100000	0010000	0001000	0000100	0000010	0000001

Table 2. Comparison of results obtained using test dataset

S NO.	INPUT PARAMETERS						ACTUAL FAULT CONDITION	FAULT IDENTIFIED	
	V_1	V_2	V_3	I_1	I_2	I_3		MLP	PNN
1	2.654937	2.619618	2.6959	0.6114231	0.5967827	0.6096965	NF	NF	NF
2	2.654646	2.619546	2.694069	0.6801607	0.6630943	0.6760761	NF	NF	NF
3	2.615218	2.618053	2.691295	0.7447775	0.7273625	0.738741	NF	NF	NF
4	2.650816	2.601661	2.673722	0.006123	0.641548	0.6385528	SP	NF	SP
5	2.650347	2.604759	2.675032	0.0061104	0.6387148	0.6352944	SP	SP	SP
6	0.9191691	2.621913	2.625237	0.1726076	0.7722042	0.6627471	UB	UB	UB
7	2.600413	1.303555	2.667813	0.6857667	0.1734909	0.7607303	UB	UB	UB
8	2.380475	2.358105	2.419025	0.3527327	0.3525339	0.3370528	UV	UV	UV
9	2.657179	2.613409	2.687374	1.671357	1.650515	1.6687	LR	LR	LR
10	2.638303	2.602147	2.674996	0.8074452	0.7878412	0.7996882	OL	OL	OL
11	2.637658	2.600486	2.673771	0.8031466	0.7825137	0.7974771	OL	OL	OL
12	2.862447	2.868324	2.851844	0.4826271	0.4987077	0.4967233	OV	OV	OV

Table 3. PNN based accuracy analysis

MAPI	MSI	RMSI	Successful Detection
0.20755	0.0002076	0.03609	99.515

The above mentioned results of Table 2 clearly demonstrate the superiority of the PNN algorithm over the Multi-Layer Perceptron algorithm. The results obtained by PNN are largely congruent with the actual fault conditions.

Conclusion

This paper discusses the progresses made in condition monitoring of 3-phase induction motor over the past few years and also proposes a novel and proficient method for identification of faults in 3-phase electrical induction motors using the Probabilistic Neural Network algorithm.

The suggested Fault Detection System (FDS) has been designed and testes using an open source dataset consisting of 788 readings. The FDS uses the 3-phase RMS voltage and current values of each reading as input to assign one of 7 possible classes to them. Along with being robust, due to the closed loop nature of the system, it is also reliable. An evaluation alongside the previously used MLP method highlights the superior performance characteristics of the proposed approach.

There are many ways of improving upon the results obtained using this algorithm in the future. One of the most obvious ways is to make use of better AI techniques such as ELM [8] and Deep learning [9]. These are up and coming methods which have been developed in recent years.

ELM (Extreme Learning Machine) is an algorithm that improves upon the performance of basic feed-forward networks while at the same time improving the prediction accuracy of the AI model. Another major advantage is that the hidden layer need not be manually tuned in this. This reduces the time required for implementation of the model since manual tuning is both error-prone as well as time-intensive. Deep learning is a type of machine learning algorithm that models high-level abstractions in data by cascading many layers of non-linear units for transformation and feature-extraction.

Another way of improving the accuracy of output prediction is to make use of a bigger dataset.

Future work based on the currently obtained results will be aimed at adapting the planned methodology for online state monitoring and fault diagnosis for 3-phase IMs to make the developed model usable in real time.

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