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Development of Integrated Softcomputing Approach for Stator Resistance Estimation of Three Phase Induction Motor

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ABSTRACT
In this paper, an integrated Quantum inspired GA (QGA) based generalized neural network (QGA-GNN) has been developed. The QGA-GNN is used for estimation of stator resistance of a 5hp Three phase Induction Motor (3Φ I.M.) under different healthy and unhealthy working conditions. The simulation model is used to collect the set of data for estimating stator winding resistance under healthy and faulty (i.e. 10%, 20%, 30% or 40% short circuited) conditions. The motor current and motor speed are considered as input and stator resistance as output of the proposed technique. The results obtained from QGA-GNN are compared with the ANN and GNN. QGA-GNN is giving good results under different working conditions. It is found that the training epochs required in ANN is about 50,000, in GNN - about 400 epochs and in QGA-GNN it is negligible. The superiority in terms of RMSE of QGA-GNN is 0.001 in comparison to ANN which is 0.012.

Keywords — Stator Resistance Estimation, Three Phase Induction Motor, Artificial Neural Network, Genetic Approach, Quantum Genetic Approach**,** Soft Computing techniques.

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I. INTRODUCTION

Three phase induction motor (3Φ I.M.) stator resistance non-linearly changes with operating conditions, like weather conditions, magnetic, electrical and mechanical couplings, etc. The precise estimation of stator resistance is necessary for good modeling and control of 3Φ I.M.

Stator resistance of a 3Φ I.M. are normally obtained by performing various tests, such as, dc test, zero-load ac test, rated shaft load and stationary rotor test for balanced operating conditions [1]. In the case of an unbalanced 3Φ I.M., like damaged rotor cage or aluminium-bars, stator resistance cannot be exact [2-4]. Some investigators have used 3Φ I.M. current frequency spectra for finding damaged bars in 3Φ I.M. [5]. Firstly, these methods are off line method for parameter estimation and secondly, they are not fault tolerant or any learning mechanism. Therefore, soft computing approaches are used.

Soft computing approaches [6], namely, ANN and its variants [7.8], Fuzzy system [9], neural fuzzy system [10], wavelet [11] and GA [12] have been used parameter identification and condition monitoring.

ANN can handle large blocks of information at a time because of its parallel processing capability. Hence, it is an effective approach for 3Φ I.M. stator resistance evaluation. But, there is no specific ANN structure and configuration for a given problem. Also it is not known that which type of neuron will be good for given problem. Hence, many neuron structures have been developed such as summation neuron, product neuron or combinations of these structures. To overcome these problems GNN was developed by Chaturvedi et.al. [13-17]. But the training issues of GNN also remain same as of ANN i.e. sufficient and good data for training, stuck in local minima if backprop training algorithm is used.

To overcome these problems and accurately estimate the 3Φ I.M. stator resistance QGA-GNN is proposed in this paper and the results are compared with ANN and GNN. This paper is divided into five sections. The first section deals with the introduction of the paper and second section introduces the soft computing and Quantum computing and development of QGA-GNN. The third section describes the methodology for estimating the stator resistance of 3Φ Induction Motor. The results and discussion are mentioned in section fourth. Finally, the paper is concluded in section fifth and the references are given.

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II. DEVELOPMENT OF QGA-GNN

A. GENERALIZED NEURAL NETWORK (GNN)

It is known from experience that the simple ANN has a range of restrictions such as large training data, long training time, and possibly large network size. To overcome these problems, a GNN has been proposed with the help of compensatory functions at aggregation and doorstep function as activation for GNN as shown in Fig.1. The back-propagation-training algorithm is used. After Learning use the GNN for 3Φ I.M. stator resistance estimation.

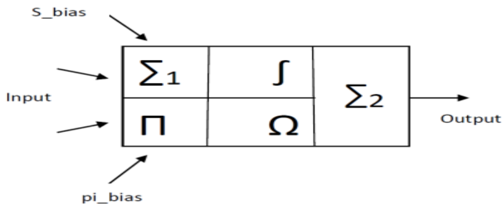

Fig.1 GNN Model

Calculation of output of GNN [13-17]

1. The output of the Σ_1 part of the generalized neuron is

$$O_{\Sigma} = \frac{1}{1 + e^{-\lambda s * s\_net}} \quad (1)$$

where $s\_net = \sum W_{\Sigma i} X_i + X_{o\Sigma}$

2. The output of the π part of the generalized neuron is

$$O_{\Pi} = e^{-\lambda p * pi\_net^2} \quad (2)$$

where $pi\_net = \prod W_{\Pi i} X_i * X_{o\Pi}$

3. The output of the generalized neuron can be written as

$$O_{pk} = O_{\Pi} * (1 - W) + O_{\Sigma} * W \quad (3)$$

The RMSE is determined by GNN output (estimated stator resistance compared with actual staotr resistance) and used for weight optimization of GNN.

B. GENETIC APPROACH (GA)

The Newton-Raphson depends mainly on starting values. If the starting values are Optimization approach is often used for stator resistance optimization, but its performance not good, optimization may take a long time or it may not converge at all. Also it needs error derivative for optimization as used in backprop. These hurdles motivated the researchers to devise a method which does not require derivative. The solution does not depend or is less dependent on the starting values. The genetic approach is such a stochastic method [18].

The objective function given in equation (4) is used by GA to optimize the weights of GNN.

F = 1/(1+RMSE) (4)

GA is a stochastic approach to find tuned solution. The only problem of GA is its slowness because it is an iterative process. To speed up GA the concepts of Quantum computing is used.

C. QUANTUM COMPUTING

The advancement in modern science offers improved computing from conventional to quantum with better calculation time, labour, and memory requirements, needed for non-polynomial hard problems. Several real time problems can be solved by genetic approach, but not with good efficiency. Hence, the present work concentrates on Quantum Genetic Approach (QGA). QGA adapts ideas of Quantum bits (Q-bits) and its superposition. The usefulness and worthiness of QGA is compared with GA.

QGA contains groups of Q-bits. Q-bit is the fundamental construction block of Q-calculation [19-20]. The QGA population is modified by different operators and optimizes the results [21-24]. QGA is used in this work for stator resistance estimation of an induction motor.

Quantum GA (QGA)

Quantum Computing (QC), proposed in the 1970s, depends upon Q-physics. The working of QC is based on Q-bits, or qubits. The QC is much faster than digital computing because it can do several operations in parallel. Q-bit sets the information as a series of Q-states such as 1 or 0, or between 1 and 0, or superposition.

QC utilizes superposition and entanglement of Q-bits. The QC can store exponentially more information than digital computer.

Consider a QC having *n*Q-bits (i.e. superposition of 2^n dissimilar states). QC modifies these Q-bits with Q-logic gates. The final result comes after converging Q-bits into any one of the 2^n clean states.

The state of a 3-Q-bit QC is an 8D vector (a, b, ... h), known as *ket*, which has complex coefficients and satisfies the condition,

$$|a|^2 + |b|^2 + |c|^2 + |d|^2 + e^2 + |f|^2 + |g|^2 + |h|^2 = 1 \quad (5)$$

In QC, a 2-D Q-bit is

$$|0\rangle = (1,0) and |1\rangle = (0,1)$$

D. QGA-GNN APPROACH (QGA-GNN)

The schematic diagram of QGA-GNN is shown in Fig. 2, in which QGA is used for training. The advantage of QGA as training algorithm is that it a stochastic learning algorithm and hence there is no need to calculate the error gradient (or derivative of error) as in the case of standard back propagation or its variants.

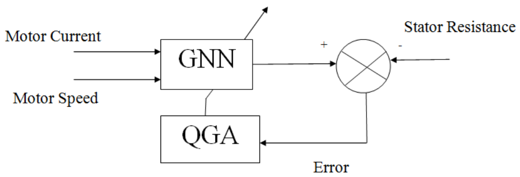

Fig. 2 Schematic diagram of QGA-GNN

In the following section the above mentioned tools have been used for stator resistance estimation of 3Φ I.M. whose specifications are given in Table 1. After Learning use the QGA-GNN for machine stator resistance estimation.

III. QGA-GNN FOR ESTIMATING THE STATOR RESISTANCE OF 3Φ INDUCTION MOTOR

This 3Φ I.M. has been used in the lab for generating real time data under different operating conditions for training the neural networks (ANN, GNN and QGA-GNN). The flowchart of methodology is given in Fig.3.

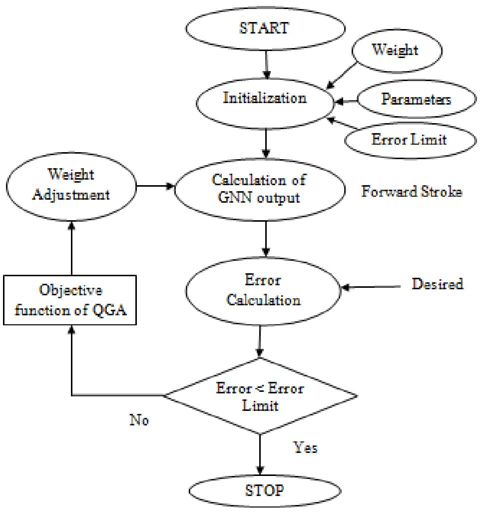

Fig.3 Flow Chart of Methodology

The QGA-GNN is trained for two inputs namely Stator Current (I_s) and Motor Speed (ω_m) and output is Stator Resistance (R_s) under different operating conditions using the following steps.

Step 1 Data Collection

Faults are created in 3Φ I.M. in computer simulation model for replicating the stator winding short circuited by 10%, 20%, 30% and 40%. The stator resistance has been calculated and substituted in the model to get motor data such as stator current motor speed for use as input of QGA-GNN. In training 70% data is used and rest 30% data is used for validation out of set of 500 data.

Step 2 Training of QGA-GNN

QGA-GNN is trained for the data generated in Step 1 using QGA algorithm. The QGA-GNN training stator resistances are illustrated in Fig. 9.

Step 3 Performance Testing of QGA-GNN

The trained QGA-GNN is tested for new input data under different operating conditions (healthy and unhealthy conditions). The Testing performance of ANN is shown in Figs. 10.

Step – 4 Comparison of QGA-GNN with other neural approachwes

GNN with backprop learning algorithms and two different ANN structures with Levenburg as mentioned in Table – 2 and 4 are also trained with the same data with the learning parameters mentioned in Table - 4. The trained ANNs have been tested. The training results are shown in Figs. 4-5. The trained ANN s and GNN are used for testing and results are shown in Fig. 6 - 8.

Table-1 Specifications of 3Φ I.M.

Number of poles	2,4,6,10,12 (By changing stator coil connections)
External dia of 3Φ I.M. Stator	25.5 cm
Internal dia of 3Φ I.M. Stator	12.18 cm
Gap between stator and rotor	0.325cm
Length of Si-steel core	6.25 cm
Dia of 3Φ I.M. shaft	3.4 cm
Rotor slot length	1.33 cm
No. of stator slots	36
No. of rotor slots	28
specified voltage (line)	440 volts
specified frequency	50 Hz
specified power	3.75kW
Skew	0.425

An ANN is used for stator resistance estimation of 3Φ I.M. The ANN structure is given in Table 2 and Learning Parameters are shown in Table 3.

Table 2 ANN– 1 Structure

Layers	**Number of Neurons**	**Activation functions**
Input layer	2	-
Unseen Layer - 1	10	tan-Sig
Unseen Layer - 2	22	tan-Sig
Production Layer	1	pure linear

Table – 3 ANN – 1 Learning Parameters

S.No.	**Learning Parameters**	**Value**
1	Number of Epochs	50
2	Momentum Factor	0.001
3	Learning rate	1.0
4	Error Goal	0.001

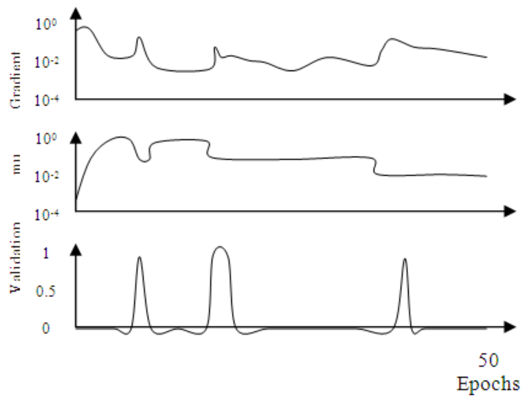

Fig. 4 ANN-1 learning Performance

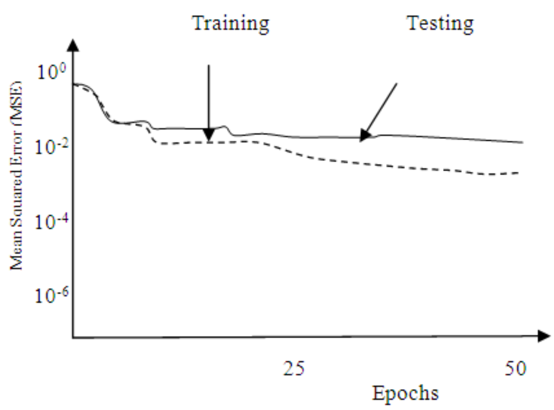

Fig. 5 Performance of the ANN- 1

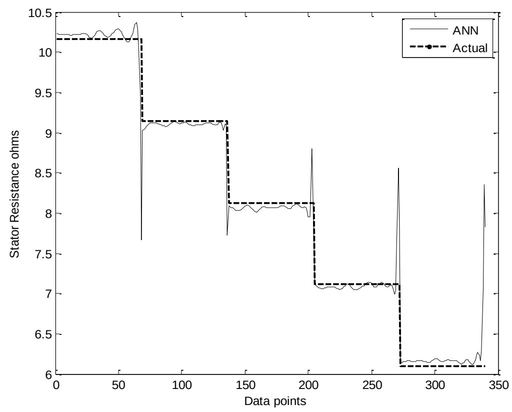

Fig. 6 Results of ANN – 1 Stator Resistance Estimator under different operating conditions (2-10-22-1)

The ANN structure is changed and tried for smaller size network as given in Table 4 with same learning parameters as used for ANN-1. The results are shown in Fig. 7 for stator resistance estimation when 3Φ I.M. is healthy, the winding(s) is (are) shorted by 10%, 20%, 30% and 40%.

Table 4 ANN -2 Structure

Layers	**Number of Neurons**	**Activation functions**
Input layer	2	-
unseen Layer - 1	6	tan-Sig
unseen Layer - 2	3	log-Sig
production Layer	1	Pure Linear

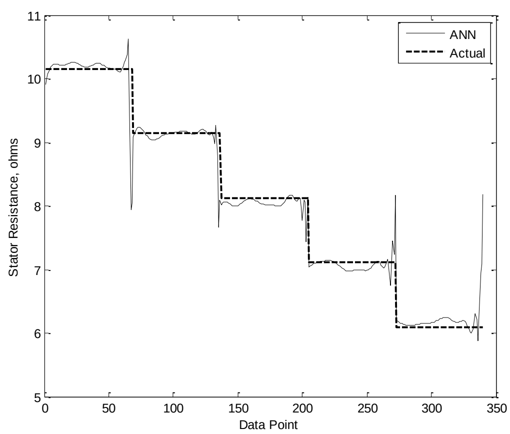

Fig. 7 Results of ANN -2 Stator resistance under different operating conditions using ANN structure (2-6-3-1)

Generalized Neural Network (GNN)
The training procedure for GNN is described below:

• Same input-output pattern as s\used in ANN-1 and ANN-2 is used to train GNN.
• Assign GNN weights in the range -0.5 to +0.5 randomly at start.
• Calculate GNN output and error, and then modify the GNN weights by a suitable training method (e.g. negative-gradient drop learning with online modifying learning parameters).
• Re-iterate the aforesaid steps for every input-output learning pattern until the error reaches less than a set value.

Once GNN has been trained, it may be used for testing.

The trained GNN is then used for 3Φ I.M. stator resistance estimation for same input as ANN and the results are shown in Fig. 8.

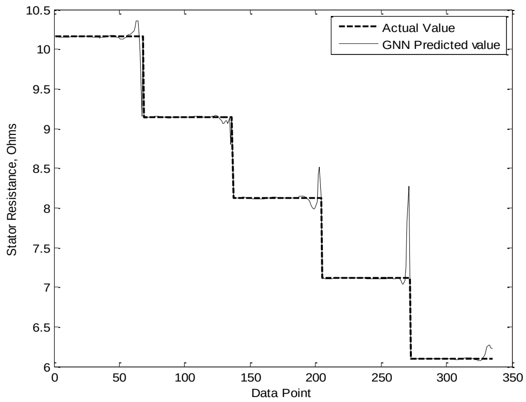

Fig. 8 Results of GNN Stator Resistance Estimation under different operating conditions

Quantum GA- GNN (QGA-GNN)

The above described QGA-GNN is used in this section for stator resistance estimation of 3Φ I.M. The GNN is trained using QGA for 500 generations and the average and maximum fitness is plotted against generation as shown in Fig. 9. It is seen that the average fitness is continuously increasing. After this training, QGA-GNN is used for estimating the stator resistance under different operating conditions as shown in Fig.10.

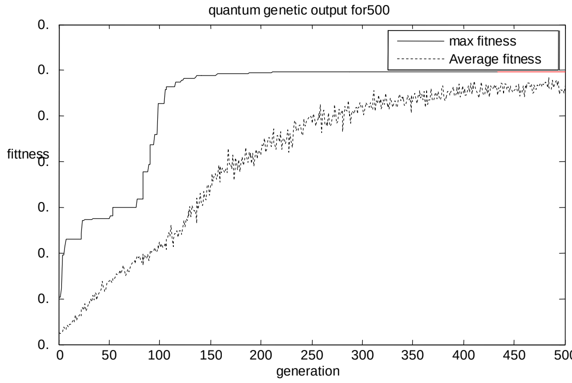

Fig.9 Training of QGA-GNN for stator resistance estimation of 3Φ I.M.

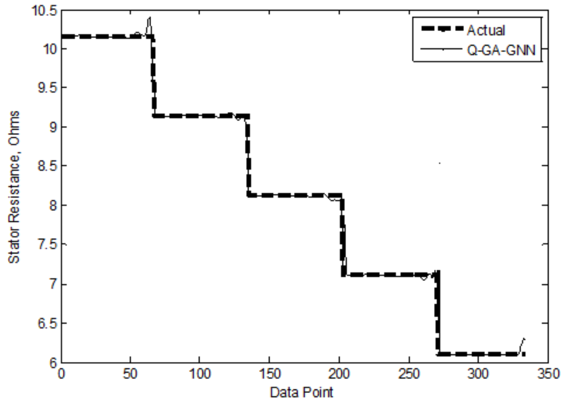

Fig. 10 Results of QGA-GNN Stator Resistance Estimation under different operating conditions

IV. RESULTS AND DISCUSSIONS

Trained QGA-GNN is used to estimate the stator resistance of a 3Φ I.M. Also two different ANN structures such as (4-6-3-1) and (4-10-22-1) are trained and used for estimating the IM stator resistance and found that no significant improvement takes place by increasing the size of the network, although the training time is drastically increased. To overcome this problem GNN with standard back-propagation training algorithm is used and it is noted that the RMS error is reduced significantly as shown in Table 5. These results provided motivation to work in stator resistance estimation using GNN and, therefore, QGA-GNN is developed. QGA, a stochastic learning algorithm, tries to reach to global optimal results. The results obtained by QGA-GNN are even better than GNN as shown in Table 6. It also portrays that single GNN is giving good results as compared to both ANN-1 and ANN-2. The training of GNN is further improved by QGA.

Table 5 Comparison of different techniques

Sl. No.	Proposed Techniques	No. of Neurons	No. of Inter-Con n.	Training Epochs required	% Max Error	% Min Error	RMS Error
1	ANN – 2 (2-6-3-1)	12	33	50204	36.7	2.35	0.012
2	ANN - 1 (2-10-22-1)	35	262	33514	33.3	2.01	0.010
3	GNN	1	6	491	17.1	1.11	0.004
4	QGA-GNN	1	6	-	3.13	0.54	0.001

Table 6 Comparison of stator resistance estimation using different techniques

3Φ I.M. Stator Resistance	Experimental Value(Ω)	ANN-2 (Ω)	ANN-1 (Ω)	GNN (Ω)	QGA-GNN (Ω)
Healthy	10.20	10.3237	10.3010	10.2387	10.2103
10% shorted	9.18	9.2930	9.2675	9.2189	9.1891
20% shorted	8.16	8.2578	8.230	8.1780	8.1742
30% shorted	7.14	7.2330	7.2069	7.1724	7.1490
40% shorted	6.12	6.1910	6.1834	6.1479	6.1320

V. CONCLUSIONS

In this paper, QGA-GNN is proposed for estimation of stator resistance of 3Φ I.M. after proper training using QGA. To train these proposed techniques, the data is generated from a mathematical model under different operating conditions such as the stator winding is healthy, or 10%, 20%, 30% or 40% short circuited under full load condition. After training, all these proposed techniques are used for stator resistance estimation for different inputs and results are compared. The stator resistance of healthy IM is 10.2 ohms, QGA-GNN is giving 10.2103 ohm and ANN -1 prediction is 10.30 ohm. It is found that QGA-GNN gives best results among all other approaches as shown in Fig. 10 and Table 6. Data clustering can be done in future work to improve the data.

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