PARAMETER ESTIMATION OF THREE PHASE INDUCTION MOTOR WITH HYBRID SOFT COMPUTING TECHNIQUES

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Abstract-*Three phase induction motors (TPIMs) are the most commonly used motors for rotating mechanical loads in the industrial environment. TPIM behavior is totally dependent on its parameters. The TPIM parameter information tells about the health of the induction motor and is also necessary for precise control of its behavior.*

A Generalized Neural Approach (GNA) trained using a hybrid approach, Quantum Genetic Algorithm (QGA), is used in this paper to estimate the parameters of the TPIM. The QGA trained GNA (Q-GNA) is then deployed for parameter estimation of a squirrel cage TPIM in the Electrical Power Research Lab, D.E.I. (Deemed University) Dayalbagh, Agra, India. Performance of The proposed method, Q-GNA, is compared with a common neural network trained using Levenberg-Marquet learning algorithm and a GNA trained using back-propagation.

***Keywords*—Parameter Estimation, Three Phase Induction Motor, Artificial Neural Network, Equivalent Circuit Parameters, Quantum Computing.**

I. INTRODUCTION

Soft computing approaches have been broadly used for three phase induction motor (TPIM) fault diagnosis. These approaches may be categorized as expert systems [1], fuzzy logic system(FLS) [2], artificial neural network (ANA) [3-8], wavelet transform [9-11], and genetic approach [12].

The TPIM parameters are not constant during its operation and change non-linearly. As the parameters vary with operating temperature and weather conditions, magnetic, electrical and mechanical couplings, etc., the parameters estimated using the methods mentioned above do not give good results [13].

In the area of electrical machines and power systems, ANA has been widely used over the past few decades [13-15, 26, 27]. ANA can handle large size information at a time because of its parallel processing capability. It can do non-linear mapping of input-output very well and extrapolate the results for ill-defined or noisy data.Thus, it can offer a viable approach for TPIM parameter estimation.

However, it has certain inherent short falls as well. ANA needs large number of examples for good training and large training time. There is no guide to specific ANA structure and configuration for a problem at hand. The neuron structure, such as summation type, or product type or combination, etc. can also be a variable. To overcome these drawbacks, a generalized neural network (GNA) is proposed in [4-5]. GNA performance can be further improved using Quantum inspired Genetic Algorithm (QGA) to overcome the learning problems.

A GNA, trained using QGA, is used for parameter estimation. Introduction of the work is provided in section one. The next four sections describe the development of QGA trained GNA, and the determination of equivalent circuit parameters of an induction motor is described in section six. Laboratory set up followed by experimental results and parameter estimation using Q-GNA, its comparison with Levenberg- Marquet learning algorithmtrained ANA and back-propagation algorithm trained GNA, and experimental results are described in section seven followed by conclusions in section eight.

II. GENERALISED NEURAL APPROACH

The GNA is built with the help of diverse compensatory functions for aggregation and different non-linear functions for activation of the GNA as shown in Fig. 1. The GNA trained using back-propagation-algorithm (BP-GNA) is used for TPIM parameter estimation.

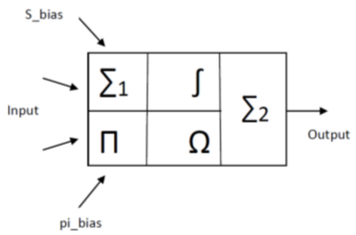

Fig-1: GNA Model

III. GENETIC ALGORITHM

Training and performance of an ANA depend heavily on starting weights. If the starting weights are not good, the optimization may take a long time or it may not converge at all. Also, optimization using back-propagation algorithm for training needs error derivative. These hurdles motivated the researchers to devise a method which does not require a derivative and the solution does not depend or is less dependent on the starting values. The genetic approach is such a stochastic method [16-19]. It mimics the procedure of natural progress in real time. Genetic algorithm (GA) has been used in the past for parameter estimation of the TPIM [20-22].

IV. QUANTUM GA

Advancements in modern science have led from conventional to quantum computing with improved calculation time, labour and memory requirements; the need for non-polynomial complex problems. Several real time problems can be solved by genetic approach, but not with good efficiency. Hence, the present work concentrates on a Quantum Genetic Approach (QGA). QGA adapts ideas of Quantum bits (Q-bits) and its superposition. The usefulness and worthiness of QGA is used to train a GNA.

Q-bit is the fundamental construction block of Q-calculation [23-24]. QGA contains group of Q-bits. The QGA population is modified by different operators to optimize the results [25]. A GNA trained using QGA (Q-GNA) is used in this work for parameter estimation of the TPIM.

V. Q-GENETIC ALGORITHM TRAINED GNA

Schematic diagram of a Q-GNA is shown in Fig. 2, in which QGA is used for training. The advantage of QGA as training algorithm is that it is 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 algorithm or its variants. Pseudo-Code for a Q-GNA is given below.

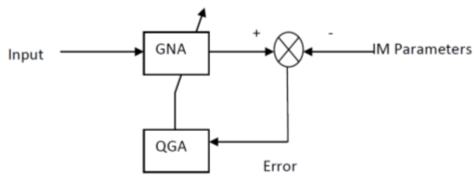

Fig-2: Schematic diagram of Q-GNA

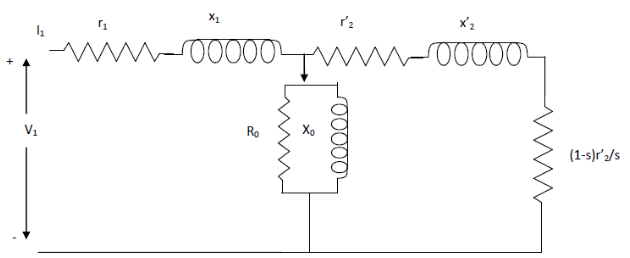

Fig-3: TPIM Equivalent Circuit

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Pseudo Codes of QGA-GNA
Begin
Initialize
    weights,
    learning parameters
    tolerable error
Loop
    Forward stroke
        Aggregation (Summation and Product) of weighted inputs for GNA
        Pass Aggregated Weighted Input through threshold function for each layer to
        Calculate output
    Reverse Stroke
        Calculate Error as the difference between Target Output and Neural Approach
        Output
        If Error <= Error Tolerance or gen >=max_gen then Stop otherwise
        Adjust the weights to minimize Error using QGA Optimization Algorithm
End
```

In the following section the above mentioned tools have been used for the parameter estimation of the TPIM.

VI. DETERMINATION OF EQUIVALENT CIRCUIT PARAMETERS OF AN INDUCTION MOTOR IN THE LAB

A delta connected TPIM is energized by balanced three phase, 415 V, 50 Hz AC supply through a three phase auto-transformer. To determine the equivalent circuit parameters of the TPIM, voltage, current and power of the TPIM are measured under the standard zero shaft load and blocked rotor test conditions, using a voltmeter, ammeter and two watt-meters. Speed of the TPIM is quite close to synchronous speed (i.e. slip is nearly zero) in the no-load test. Parameters of the common TPIM equivalent circuit, Fig. 3, are computed using the well-known procedure in the laboratory. In Fig. 3,

Z_o- no load impedance in ohms,
R_o-no load resistance in ohms,
X_o-no load reactance in ohms.
Z_b-equivalent impedance in ohms,
R_b-equivalent resistance in ohms = r_1+r_2',
r_1- Stator resistance in ohms
r_2- Rotor resistance in ohms referred to stator side
X_b-equivalent reactance in ohms = x_1+x_2'.
x_1- Stator reactance in ohms
x_2- Rotor reactance in ohms referred to stator side

VII. PARAMETER ESTIMATION USING ANA, BP-GNA AND Q-GNA

Parameters calculated from the open circuit and blocked rotor tests are used as input for the training of an ANA, a BP-GNA and Q-GNA. These trained neural networks are then used for estimating the values of Ro, Xo, R_b and X_b on-line. Structure of the ANA, BP-GNA and Q-GNA used for on-line parameter estimation is given in Table 1 and the results are compared in Table - 2.

Table-1: ANA, BP-GNA and Q-GNA structures

S.No.	Structure	ANA	BP-GNA/ Q-GNA
1	Inputs	3	3
2	Outputs	4	4
3	Hidden neurons	10	-
4	Hidden layer Activation Function	***tan sigmoidal***	***tan sigmoidal and gaussian***
5	layer Activation Function	Pure linear	Pure linear

A. *PARAMETER ESTIMATION USING ANA*

The voltage, current and power are acquired on-line and the parameters of the TPIM estimated on-line using the Levenberg-Marquet learning algorithm trained ANA are given in Table 2.

The simulated response of TPIM using ANA estimated parameters at 100% load is compared with actual results as shown in Figs. 4 through 8 for torque-speed, output power vs. speed, power factor vs speed, motor current vs speed and efficiency vs speed curves.

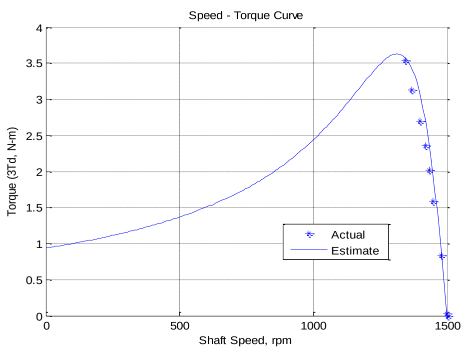

Fig-4: Speed -Torque Curve of TPIM

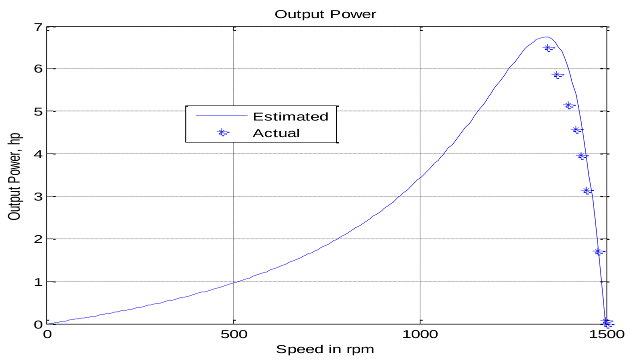

Fig-5: Output Power - Speed curve of TPIM

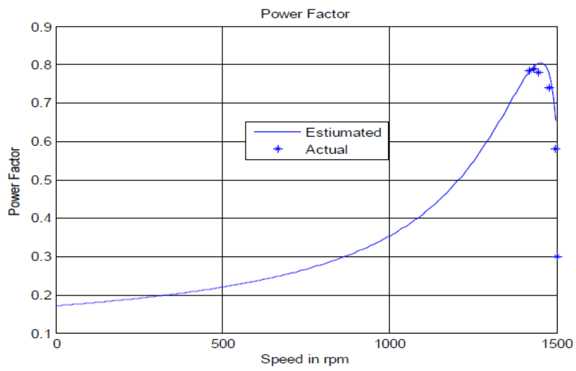

Fig-6: Power factor Vs. Speed of TPIM

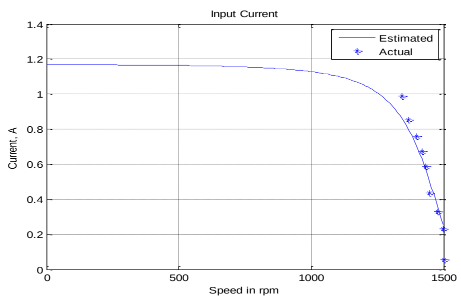

Fig-7: Motor Current Vs Speed of TPIM

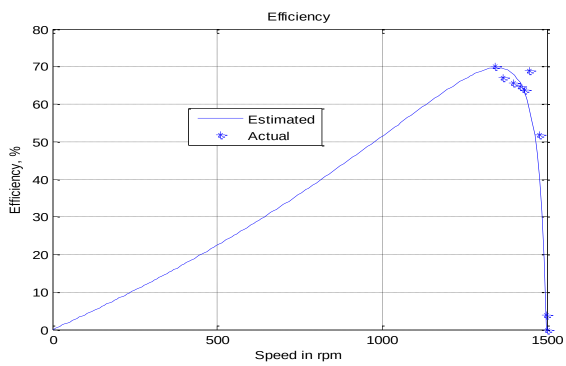

Fig-8: Efficiency Vs. Speed of TPIM

Table-2: Comparison of Experimental & Estimated Values using ANA GNA and Q-GNA at 100% load

TPIM Parameters	Experimental Value(Ω)	Estimated Value by ANA (Ω)	Estimated Value by GNA (Ω)	Estimated Value by Q-GNA (Ω)
Ro	21.1	24.3	22.1	21.4
Xo	195.38	200.46	198.5	195.5
Rb	23.011	25.01	24.12	23.5
Xb	45.59	48.59	46.57	46.5

B. *PARAMETER ESTIMATION USING BP-GNA*

The voltage, current and power is acquired on-line and the TPIM parameters are estimated on-line using ANA and GNA. The results are tabulated in Tables 3 and 4.

The speed- torque curve for these estimated parameters are compared with experimentally calculated parameters of healthy TPIM is shown in Fig. 9.

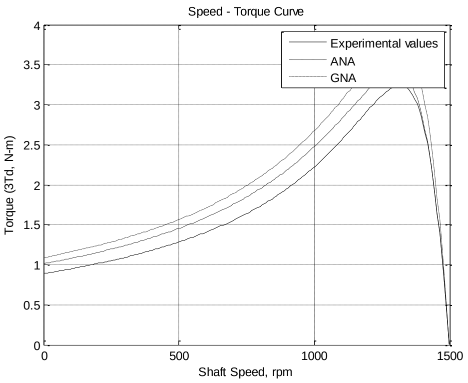

Fig-9: Comparison of speed – torque curves of TPIM for ANA, GNA and experimentally calculated parameters

Table-3: Parameter Estimation under different loading conditions using ANA

	Loading condition					
% Load	0%	25%	50%	75%	100%	150 %
Ro	19.55	20.05	21.07	22.7	24.3	24.5
Xo	182.4	185.8	190	196	200.46	209
Rb	22.61	22.78	22.88	22.9	25.01	23.9
Xb	44.84	45.22	46.62	47.8	48.59	50

Table–4: Parameter Estimation under different loading conditions using GNA

	Loading condition					
% Load	0%	25%	50%	75%	100%	150%
Ro	19.75	20.15	21.47	21.5	22.1	23.1
Xo	183.1	186.4	190.8	197	198.5	200
Rb	22.71	22.98	23.18	23.2	24.12	24.9
Xb	45.14	45.52	46.82	48.9	46.57	51

C. *PARAMETER ESTIMATION USING Q-GNA*

The voltage, current and power is acquired on-line and the TPIM parameters are estimated on-line using Q-GNA and the results are given in Table 5. The speed-torque curves for these estimated parameters are compared with experimentally calculated parameters of healthy TPIM are shown in Fig. 10.

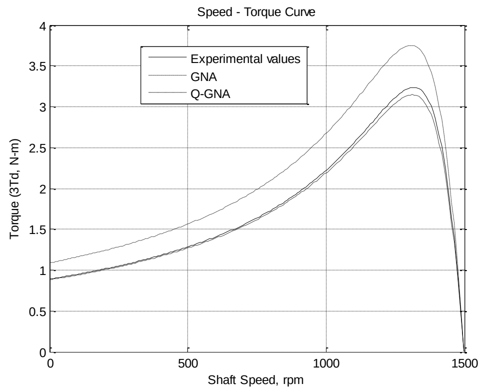

Fig-10: Comparison of speed – torque curves of TPIM for BP-GNA, Q-GNA and experimentally calculated parameters

Table –5: Parameter Estimation under different loading conditions using Q-GNA

	Loading condition					
	0%	25%	50%	75%	100 %	150%
Ro	19.75	20.3	20.6	21.1	21.4	21.11
Xo	183.1	186.41	190.8	194.5	195.5	212
Rb	22.71	22.99	23.28	23.4	23.5	24.1
Xb	43.24	44.62	44.82	45.8	46.5	51.2

VIII. CONCLUSIONS

This paper deals with the experimentation on TPIM under different motor conditions and also different loading conditions. It is found that the phase currents of TPIM are very different for different motor conditions and under different loading conditions. The information for motor currents, voltages, and power are used for on-line estimating the motor parameters R_b, X_b, and shunt parameters R_0 and X_0 of TPIM. The parameter estimation is done with neural approach such as ANA, GNA, Q-GNA and compared with conventional methods.

The estimated parameters using proposed approaches have been used by the mathematical model of TPIM to plot the ω-T characteristics for validating the results.
It is found that the results obtained from Q-GNA are better than other approaches ANA and GNA as shown in Figs. 10 and Tables 3-5.

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BIOGRAPHIES

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