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Cascaded ANN for Evaluation of Frequency and Air-gap Voltage of Self-Excited Induction Generator

Raja Singh Khela, R. K. Bansal, K. S. Sandhu, and A. K. Goel

***Abstract*—**Self-Excited Induction Generator (SEIG) builds up voltage while it enters in its magnetic saturation region. Due to non-linear magnetic characteristics, the performance analysis of SEIG involves cumbersome mathematical computations. The dependence of air-gap voltage on saturated magnetizing reactance can only be established at rated frequency by conducting a laboratory test commonly known as synchronous run test. But, there is no laboratory method to determine saturated magnetizing reactance and air-gap voltage of SEIG at varying speed, terminal capacitance and other loading conditions. For overall analysis of SEIG, prior information of magnetizing reactance, generated frequency and air-gap voltage is essentially required. Thus, analytical methods are the only alternative to determine these variables. Non-existence of direct mathematical relationship of these variables for different terminal conditions has forced the researchers to evolve new computational techniques. Artificial Neural Networks (ANNs) are very useful for solution of such complex problems, as they do not require any a priori information about the system. In this paper, an attempt is made to use cascaded neural networks to first determine the generated frequency and magnetizing reactance with varying terminal conditions and then air-gap voltage of SEIG. The results obtained from the ANN model are used to evaluate the overall performance of SEIG and are found to be in good agreement with experimental results. Hence, it is concluded that analysis of SEIG can be carried out effectively using ANNs.

***Keywords*—**Self-Excited Induction Generator, Artificial Neural Networks, Exciting Capacitance and Saturated magnetizing reactance.

I. INTRODUCTION

RAPIDLY depleting rate of conventional energy sources, has led the scientists to explore the possibility of utilizing non-conventional energy sources. Wind energy, largely available in our atmosphere, can be harnessed to generate electric power using induction generator. Brush-less rotor construction, absence of separate source for excitation, ease of maintenance and reduced unit cost are some of the major advantages of induction generator that makes it suitable for power generation particularly in remote areas. Moreover, induction machine when connected across capacitor bank and driven from wind turbine with varying speed is capable of generating power as SEIG. The output frequency and voltage of machine are highly dependent on its parameters, speed, terminal capacitance and load impedance that limits its performance.

The self excitation phenomena of induction machine is well known since 1935, when Basset and Potter reported that the induction machine can be operated as an induction generator in isolated mode by using external capacitor [1]. An approximate method of analysis of SEIG, by separating the real and reactive parts of the circuit has been reported in the literature [2]. Series capacitors have been used across the stator of SEIG to improve voltage across the load [3]. Barkle and Fergusen discussed the analysis of SEIG using modified synchronous machine transient theory and static correction to avoid over-voltage [4].

Murthy et al. have suggested an analytical technique, in which loop impedance method is used to solve the equivalent circuit [5]. On simplification, two polynomials are obtained by separating the real and imaginary parts. These polynomials are solved for saturated magnetizing reactance and generated frequency by Newton–Raphson method. Chan presented two solution techniques to predict the performance of SEIG [6]. First technique employs a novel transformation to yield 7th degree polynomial in terms of per unit frequency, whose solution enables the performance evaluation of SEIG. The second technique employs symbolic programming approach for derivation and solution of the polynomial for generated frequency. Various techniques for evaluating frequency and magnetizing reactance of SEIG have been reported in the literature [7]-[11].

Many techniques referred above involve higher order polynomials in terms of generated frequency and magnetizing reactance, whose coefficients are determined by solving the impedance network of equivalent circuit of SEIG (shown in Fig. 1). The equations having complex elements are very lengthy and prone to errors. To overcome these difficulties, alternate methods are being developed for the performance evaluation of SEIG. Sandhu and Jain developed an equivalent circuit of SEIG by replacing the rotor circuit with an active voltage source and internal impedance. It makes the SEIG analysis simpler and computationally economical [11].

Artificial Intelligence (AI) techniques, the recent

Manuscript received in February, 2007. This work was supported by the grant from AICTE, New Delhi, Govt. of India, TAPTEC project TAP (325).

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computational tools are gaining importance in the field of engineering and are finding increased application in the field of power systems, operation, control and protection [12]-[14]. Artificial Neural Networks can be used to approximate any function to an arbitrary degree of accuracy. In this paper, ANNs have been used to model the behavior of the machine.

II. Equivalent Circuit Representations for Steady State Analysis of SEIG

The induction generator has no field winding to provide necessary excitation unlike in conventional synchronous alternators. Thus, excitation is supplied either by power system to which it is connected or by shunt capacitors connected across its stator. Excitation to the induction machine when supplied by the capacitor bank makes the operation of machine as self-excited induction generator.

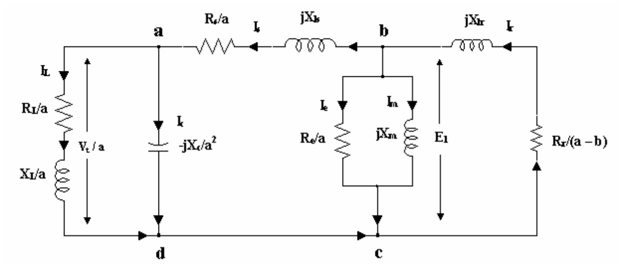

Fig. 1 Conventional equivalent circuit of SEIG without active voltage source

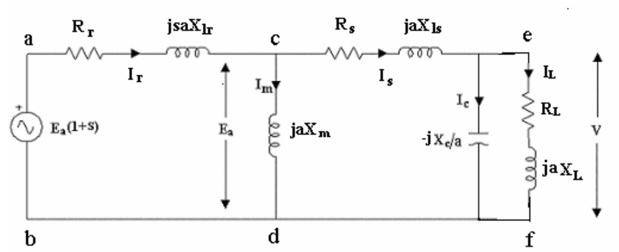

Fig. 2 Per phase equivalent circuit of SEIG with active voltage source

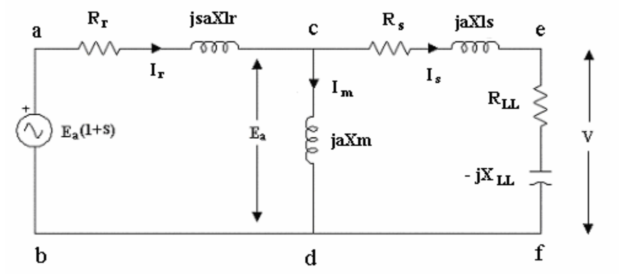

Fig. 3 Per phase simplified equivalent circuit of SEIG with active voltage source

The conventional equivalent circuit shown in Fig. 1, (used by most of the researchers for performance analysis of SEIG) does not corroborate generator operation in the absence of active voltage source [5]–[10]. Thus, equivalent circuit shown in Fig. 2 with active source is used for performance analysis of SEIG [11]. Core loss branch has been omitted due to its insignificant effect on the performance of machine. Lesser computational effort is required to evaluate magnetizing reactance and frequency using simplified per phase equivalent circuit of SEIG as shown in Fig. 3. It saves time and effort needed to generate data required for training of ANNs.

III. Simplified Equivalent Circuit of SEIG with Active Voltage Source

Equivalent circuit of SEIG shown in Fig. 2 is further simplified by replacing the parallel combination of load impedance $(Z_L = R_L + j\,a\,X_L)$ and capacitive reactance $(-jX_c / a)$ with an equivalent per phase series elements as shown in Fig. 3. Expression for equivalent load resistance and reactance for lagging power factor load is given below:

$$R_{LL} = \frac{R_L X_c^{\,2}}{a^2 R_L^{\,2} + (a^2 X_L - X_c)^2}$$

$$X_{LL} = \frac{aR_L^{\,2} X_c + aX_L X_c (a^2 X_L - X_c)}{a^2 R_L^{\,2} + (a^2 X_L - X_c)^2}$$

For unity power factor, equivalent load resistance and reactance is obtained by substituting $X_L = 0$ in the above expressions. Thus net impedance across 'e and f ' becomes:

$Z_{LL} = R_{LL} - jX_{LL}$

(- ve sign indicates capacitive effect)

Combining load and stator impedance we get:

$R_{1L} = R_s + R_{LL}$

$X_{1L} = aX_{ls} - X_{LL}$ and $|X_{LL}| > |aX_{ls}|$

Nodal analysis of the circuit of Fig. 3, seen from node 'c' gives two equations by separating the real and imaginary parts.

Real part:

$$\frac{R_{1L}}{(R_{1L}^{\,2} + X_{1L}^{\,2})} - \frac{sR_r}{(R_r^{\,2} + s^2 a^2 X_{lr}^{\,2})} = 0 \qquad (1)$$

Imaginary part:

$$\frac{s^2 a\, X_{lr}}{(R_r^{\,2} + s^2 a^2 X_{lr}^{\,2})} + \frac{X_{1L}}{(R_{1L}^{\,2} + X_{1L}^{\,2})} + \frac{1}{aX_m} = 0 \qquad (2)$$

Simplifying equation (1), a quadratic equation in terms of slip is obtained as given below:

$$As^2 + Bs + C = 0 \qquad (3)$$

where $A = a^2 X_{lr}^{\,2} R_{1L}$

$B = -R_r (R_{1L}^{\,2} + X_{1L}^{\,2})$

$C = R_r^{\,2} R_{1L}$

Saturated magnetizing reactance X_m is evaluated by solving equations (1) and (2).

TABLE I
RANGE OF MACHINE PARAMETERS AND TERMINAL VARIABLES FOR TRAINING ANNS
TRAINING PARAMETERS: TRAINING SAMPLES = 4000, INITIAL LEARNING RATE = 0.001

Machine Parameters (pu)		Terminal Variables (pu)	
Parameter	Range	Parameter	Range
stator resistance, r_s	0. 02 – 0.10	speed, b	0.90 – 1.10
rotor resistance, r_r	0.02 – 0.10	capacitance, c	0.60 – 0.80
stator reactance, x_{ls}	0.04 – 0.15	load conductance, $1/r_l$	0.01 – 1.00
rotor reactance, x_{lr}	0.04 – 0.15		

$$X_m = \frac{-R_r(R_{1L}^{\ 2} + X_{1L}^{\ 2})}{(s\,a^2 X_{lr} R_{1L} + a\,R_r X_{1L})} \tag{4}$$

The relation between per unit frequency ‘a’ and speed ‘b’ is written as:

$$a = b/(1+s) \qquad a < b \tag{5}$$

Unknown values of magnetizing reactance ‘X_m’ and generated frequency ‘a’ is obtained by solving equations 1 to 5. Further, computed value of X_m is used to determine the air gap voltage ‘E_1’ at rated frequency using magnetizing characteristics of the induction machine [Appendix-I]. Once magnetizing reactance and generated frequency are computed, the performance of SEIG can be evaluated for given terminal conditions from equivalent circuit given in Fig. 2.

IV. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is an information-processing paradigm that is inspired by the computational methods used by human brain. The human brain is made up of innumerable number of nerve cells called neurons. Each neuron acts as small processing element. ANNs try to replicate this biological neural network. Large numbers of these neurons, the elementary processing elements, are highly interconnected and work in unison to solve complex problems. ANNs, like human being, learn by example. An ANN is configured for a specific application, through a learning process. Learning in ANNs involves change in interconnection weights between different neurons.

Although, artificial neural network (ANN) is relatively recent concept, immense research has been conducted in this field. Application of ANNs has been reported for estimation of bus bar voltage in distribution systems and to model the behavior of electric machines [12]–[13]. ANNs find a wide variety of applications in diverse areas including functional approximation, non-linear system identification, and control [14]-[16]. In this paper, Multilayer Perceptron (MLP) type neural network is used. In MLP, the neurons are arranged in different layers. The first layer is called input layer and contains neurons equal to number of inputs. Output layer contains neurons equal to number of outputs. The number of neurons in the hidden layer is chosen so as to get the optimal performance of the network.

Fig. 4 represents the arrangement of neurons and their inter-connections in different layers. Input data is presented to first layer and then passed on to hidden layer. After processing this data, the output of the hidden layer is passed on to output layer of network to yield the desired output. The input to any neurons is processed using sigmoid function, $y(x) = 1/(1+e^{-x})$, where ‘x’ is the total input to a neuron. The neuron generates output between 0 and 1. Therefore, it is necessary to normalize the input-output data.

V. ANN IMPLEMENTATION OF SEIG

It is observed that for well-designed induction machine the slip varies from two to six percent. For variable speed operation of self-excited induction generator, the range of speed is chosen to vary from 90% to 110% to keep the frequency within acceptable limits. Similarly the range of load is taken to vary from no load to full load. For this particular case the range of stator and rotor resistance is chosen from 0.02 to 0.10 pu where as leakage reactance of stator and rotor is chosen to vary from 0.04 to 0.15 pu. This will make the analysis of SEIG more flexible in terms of range for machine parameters.

The ANN model of SEIG is trained using Multilayer Perceptron (MLP). The cascaded ANN has two stages. Both networks have single hidden layer. The input layer of 1st neural network has seven neurons accounting for seven inputs namely: stator resistance ‘R_s’, rotor resistance ‘R_r’, stator leakage reactance ‘X_{ls}’, rotor leakage reactance ‘X_{lr}’, speed ‘b’, capacitance ‘C’ and load conductance ‘$1/R_L$’. The output layer has two neurons that account for the two outputs namely: generated frequency ‘a’ and saturated magnetizing reactance ‘X_m’. The hidden layer is chosen to have 10 neurons, thereby making ANN architecture as 7-10-2.

Five thousand training data samples are generated for training the ANN. The input-output data for training the ANN model of SEIG is obtained using analytical technique [11] that requires very small computational effort. The training data is obtained for the specified range of machine of parameters and other terminal condition as mentioned in Table I. Network is trained using Levenberg-Marquardt training algorithm with initial learning rate 0.01 and sum-square error (SSE) goal is set at 0.0075. The SSE goal is achieved in 734 epochs of training. The performance of first ANN network is tested with input data samples (other than training samples) of machine parameters, speed and load selected randomly while the

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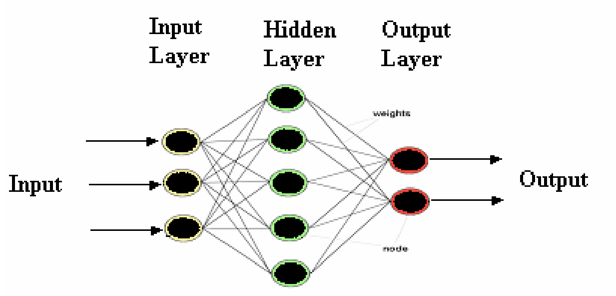

Fig. 4 Architecture of multilayer perceptron

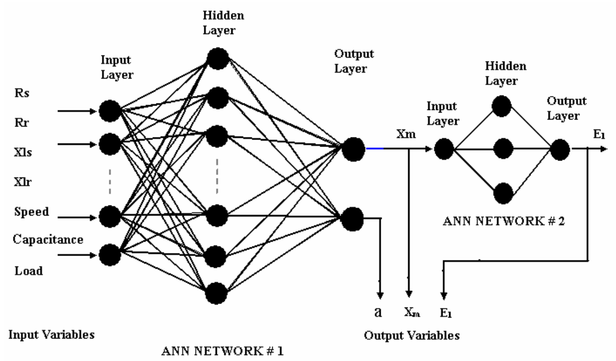

Fig. 5 Cascaded artificial neural network

capacitance is varied from 0.60 to 0.80 pu. The output results obtained from the first network with randomly selected test data are shown in Fig. 6(a) & (b).

The second network is trained with the input-output data (twenty samples) obtained experimentally from the experimental machine. The magnetizing characteristics of the machine obtained from piece wise linearization of the experimental data are given in Appendix-I. Training is given to the network having one neuron each in input and output layer accounting for saturated magnetizing reactance X_m and air gap voltage E_1 respectively. The hidden layer has three neurons. Thus, ANN architecture for second network is 1-3-1, shown in Fig. 5. Second neural network is trained with Successive Over-Relaxation Resilient Backpropagation (SORPROP) training algorithm [17]. The learning rate is set at 0.01 for both the layers. The sum square error (0.0025) for twenty training samples is obtained in 296 epochs. The performance of the second network is tested with the validation data (samples other than training samples).

ANN model of SEIG is implemented on the experimental machine [Appendix-I] with resistive loading. The machine parameters (four), speed, terminal capacitance and load are applied as input to the first network of the ANN model. Magnetizing reactance and generated frequency are obtained as output of this network. One output variable i.e. magnetizing reactance of the first network is applied as input of the second network, which yielded per phase air-gap voltage as its output. Thus, three outputs namely: magnetizing reactance, generated frequency and air-gap voltage are obtained from the cascaded ANN model of SEIG which are required for the overall analysis of the SEIG.

The performance analysis of SEIG is carried out using outputs of ANN model and solving equivalent circuit given in Fig. 2.

Slip‘s’ of machine operating as generator is obtained from the relation between per unit frequency and speed.

$s = (b/a - 1)$

For resistive load taking $X_L = 0$ we get:

$$Ir = \frac{s\,a\,E_1}{(R_r + jsaX_{lr})} \tag{6}$$

$$I_s = \frac{aE_1}{R_{1L} + jX_{1L}} \tag{7}$$

$$I_m = \frac{E_a}{jaX_m} \tag{8}$$

$$I_L = I_s \frac{-jX_c/a}{R_L + j(aX_L - X_c/a)} \tag{9}$$

$$I_c = I_s \frac{R_L + j\,a\,X_L}{R_L + j(aX_L - X_c/a)} \tag{10}$$

$$V = E_a - I_s(R_s + j\,aX_{ls}) \tag{11}$$

$$P_o = 3I_L^2 R_L \tag{12}$$

VI. Results and Discussions

In this section, the output results obtained from ANN model of SEIG are discussed. Randomly selected machine parameters and other terminal variables that includes speed, resistive load and terminal capacitance, are applied to the first stage of ANN model to obtain its output corresponding to input variables. To validate the performance of ANN model, the results obtained from ANN model are first compared with analytical solution by choosing random values of machine parameters, speed, load and varying terminal capacitance value from 0.60 to 0.80 (8 samples). For three set of randomly selected inputs, the mean SEE, minimum mean SSE and standard deviations of output results of ANN model from analytical solution are recorded in Table II While comparing output results of first stage of ANN model with analytical solution, it is observed that for first set of inputs, the mean SSE for generated frequency and magnetizing reactance are recorded to be 2.5361 x 10^{-7} and 1.4113×10^{-5} respectively. For second and third sets, the values of mean SSE for generated frequency are 9.3712×10^{-7} & 2.5146×10^{-7}, while for magnetizing reactance the mean SSE reported is 7.3218×10^{-5} & 0.8691×10^{-5}.

To further investigate the effectiveness of ANN model, output of ANN model is also determined with parameters of experimental machine, running at rated speed (1500 rpm), supplying resistive load (R_L = 350 ohms) and varying terminal capacitance from 0.60 to 0.80. It is observed that the mean

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TABLE II
DETAIL OF DEVIATIONS OF RESULTS OBTAINED FROM ANN MODEL OF SEIG AND ANALYTICAL RESULTS

Set No.	Randomly Selected Machine Parameters (pu)	Randomly Selected Terminal Variables (pu)	Capacitance Variation	MSSE * Generated Frequency	MSSE * Magnetizing Reactance
1	R_s = 0.0535, R_r = 0.0877 X_{ls} = 0.0984, X_{lr} = 0.0625	speed =1.0222 load conductance (1/ R_L) = 0.1958	0.60 – 0.80	$2.5361x10^{-7}$	$1.4113x10^{-5}$
2	R_s = 0.0602, R_r = 0.0768 X_{ls} = 0.0877, X_{lr} = 0.0738	speed = 0.9345 load conductance (1/ R_L) = 0.6931	0.60 – 0.80	$9.3712x10^{-7}$	$7.3218x10^{-5}$
3.	R_s = 0.0474, R_r = 0.0432 X_{ls} = 0.0779, X_{lr} = 0.0993	speed = 1.0879 load conductance (1/ R_L) = 0.8916	0.60 – 0.80	$2.5146x10^{-7}$	$8.6910x10^{-6}$

generated frequency:

minimum MSSE = $2.5146x10^{-7}$
maximum MSSE = $9.3712x10^{-7}$
mean sum-squired error = $4.8073x10^{-7}$
standard deviation = $3.9525x10^{-7}$

magnetizing reactance:

minimum MSSE = $8.6910x10^{-6}$
maximum MSSE = $7.3218x10^{-5}$
mean sum-squired error = $3.2007x10^{-5}$
standard deviation = $3.5792x10^{-5}$

*Mean SSE for 10 samples of input variables.

TABLE III
DETAIL OF DEVIATIONS OF RESULTS WITH EXPERIMENTAL MACHINE PARAMETERS, SPEED, LOAD AND VARYING CAPACITANCE

Machine parameters and terminal conditions:

stator resistance, R_s = 0. 0601 pu
stator reactance, X_{ls} = 0. 0978 pu
rotor resistance, R_r = 0. 0437 pu
rotor reactance, X_{lr} = 0. 0978 pu

speed = 1500 Rpm (1.0 pu)
load resistance = 350 ohms (3.67 pu)
no. of samples = 8

Output Variables	Sum–squared Error (SSE)	Minimum SSE	Maximum SSE	Mean SSE	Standard Deviation
magnetizing reactance	$8.5683x10^{-5}$	$1.6799x10^{-7}$	$4.0761x10^{-5}$	$1.0710x10^{-5}$	$1.3074x10^{-5}$
generated frequency	$9.8113x10^{-7}$	$5.6461x10^{-9}$	$3.2396x10^{-7}$	$1.2264x10^{-7}$	$1.1330x10^{-7}$
air-gap voltage	$1.0069x10^{-5}$	$4.5918x10^{-8}$	$4.4292x10^{-6}$	$1.2586x10^{-6}$	$1.3987x10^{-6}$

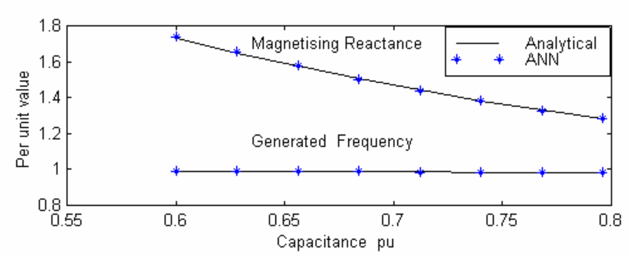

Fig. 6 (a) Variation of magnetizing reactance & generated frequency with capacitance

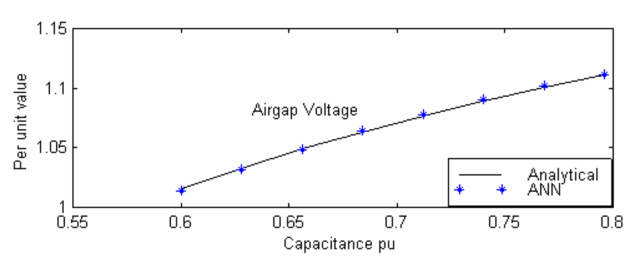

Fig. 6 (b) Variation of air-gap voltage with capacitance

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SSE for magnetizing reactance and generated frequency are. 1.0710×10^{-5} & 1.2264×10^{-7} respectively where as standard deviation for these two variables are recorded to be 1.3074×10^{-5} & 1.1330×10^{-7}. The deviations of ANN results from the analytical results are quite insignificant as given in Table III. Thus, it is established that result of ANN model are consistent with conventional techniques.

Output of the first stage of ANN is applied to the input of the second stage of network to give air-gap voltage as its output. The input of the second stage is magnetizing reactance. ANN model of SEIG is tested with parameters of experimental machine and a set of terminal conditions given in Table III. The output results obtained from ANN model are compared with analytical solution. It is observed that mean SSE and standard deviation for air gap voltage is recorded to be 1.2586×10^{-6} & 1.3987×10^{-6} respectively. The values of deviations are very small and insignificant, thus indicate that the results are quite accurate and consistent. The variation of magnetizing reactance, frequency and air-gap voltage with capacitance are plotted in Fig. 6 (a) & (b) for parameters of experimental machine, rated speed, (1500 rpm) and resistive load (R_L= 350 ohms) with variable capacitance from 0.60 pu to 0.80 pu.. It is observed from the results that variation of terminal capacitance does not affect the generated frequency, but air-gap voltage increases with increase in terminal capacitance

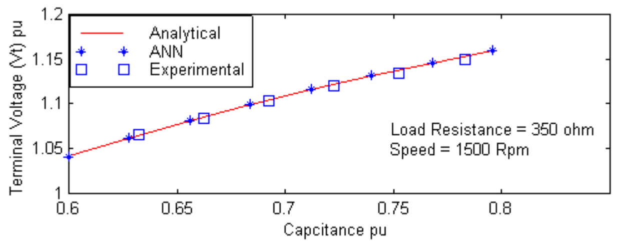

Fig. 7 Variation of terminal voltage with capacitance

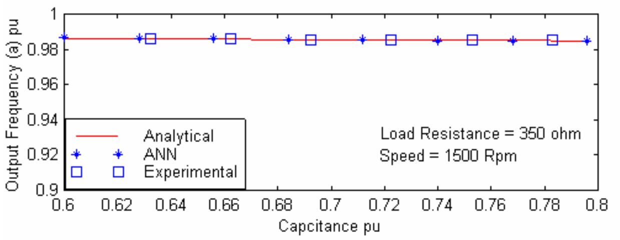

Fig. 8 Variation of output frequency with capacitance

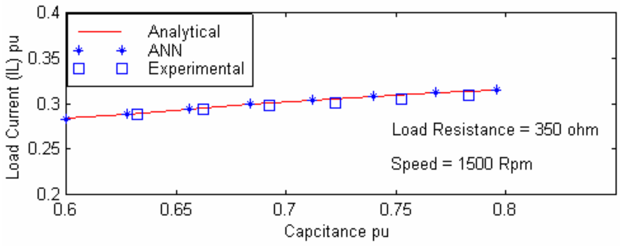

Fig. 9 Variation of load current with capacitance

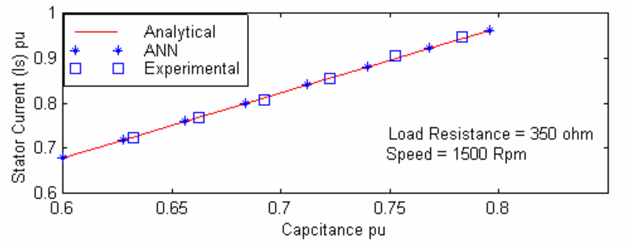

Fig. 10 Variation of stator current with capacitance

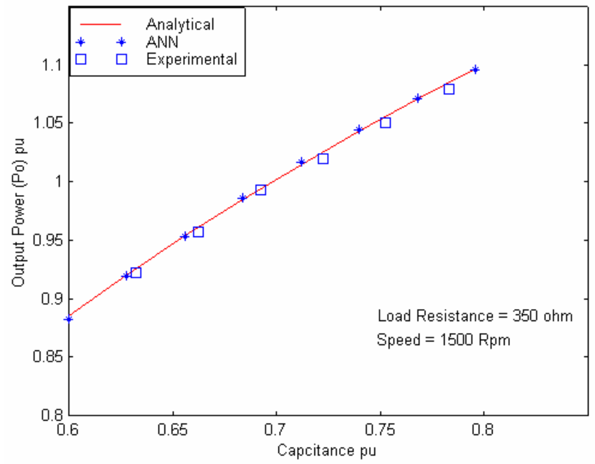

Fig. 11 Variation of output power with capacitance

VII. Experimental Verification of Performance of SEIG

From the closeness of output results with the analytical solution, it is concluded that ANN model of SEIG can be used for evaluating the frequency, magnetizing reactance and air gap voltage effectively. Further, the output of the ANN model can be used to determine the overall performance of the SEIG by solving equivalent circuit of Fig. 2. Using the results of ANN model, terminal voltage, generated frequency, load current, stator current and output power of SEIG is evaluated at rated speed, (1500 rpm), resistive load (R_L= 350 ohms) with variable capacitance from 0.60 pu to 0.80 pu. The results obtained are compared with experimental data obtained from the machine with same terminal conditions. From the Figures 7 to 11, it is clear that ANN results are in close agreement with experimental results.

VIII. Conclusion

Artificial Neural Networks have been implemented to analyze the steady state behavior of SEIG with varying terminal capacitance at rated speed with constant resistive load. It is observed from the results that variation of terminal capacitance does not affect the generated frequency but air-gap voltage of SEIG increases with increase in terminal capacitance. Cascaded ANNs are used for the analysis. It is also observed that though neural network is trained with randomly chosen samples but it is fully capable of computing the three un-known performance variables i.e. magnetizing

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reactance, generated frequency and air-gap voltage for any of the randomly chosen combinations of machine parameters, speed, capacitance and load. The SEIG analysis obtained using results of ANN model are compared with that obtained experimentally and are found to be in close agreement.. The results thus, obtained confirm the validity of the ANN model. Therefore, it is concluded that SEIG analysis can be carried out effectively using ANNs.

APPENDIX -I

Nomenclature

R_s , X_{ls} = per phase stator resistance and reactance.

R_r , X_{lr} = per phase rotor resistance and reactance referred to stator.

R_L , X_L = per phase load resistance and inductive reactance.

X_c = per phase capacitive reactance.

X_m = per phase saturated magnetizing reactance

a = ratio of generated frequency to the rated frequency.

b = ratio of actual rotor speed to the synchronous speed corresponding to rated frequency

s = slip of machine.

E_1 = per phase air gap voltage at rated frequency.

E_a = aE_1, per phase air gap voltage at generated frequency

$E_a(1+s)$ = per phase air gap voltage at generated frequency corresponding to mechanical power transformed to electrical power through rotor.

All quantities referred above are per unit values.

a) Machine Specifications:

$$HP = 5.0 \qquad P = 4$$
$$V_{base} = 415\ Volts \qquad I_{base} = 4.33\ Amp$$
$$P_{base} = V_{base}\, I_{base} \qquad N_{base} = 1500\ RPM$$
$$Z_{base} = 95.84\ \Omega \qquad F_{base} = 50\ Hz$$
$$C_{base} = 33.21\ \mu F$$

b) Machine parameters in ohms:

$$R_S = 5.76\ \Omega \qquad R_r = 4.19\ \Omega$$
$$X_{ls} = 9.37\ \Omega \qquad X_{lr} = 9.37\ \Omega$$

c) Magnetizing characteristics of machine:

$$for\ \ X_m < 2.6930, \quad E_1 = 1.3818 - 0.2117 X_m$$
$$for\ X_m < 2.8386\ \&\ X_m >= 2.6930, \quad E_1 = 2.1697 - 0.5057 X_m$$
$$for\ X_m < 2.9716\ \&\ X_m >= 2.8386, \quad E_1 = 3.8732 - 1.1057 X_m$$
$$for\ X_m > 2.9716, \quad E_1 = 0$$

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