Application of Artificial Neural Network for Analysis of Self-Excited Induction Generator

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ABSTRACT

It is observed that conventional techniques to analyse the steady state analysis of Self-Excited Induction Generator (SEIG) involve cumbersome mathematical procedures. In this paper an Artificial Intelligence (AI) technique has been used to analyse the behaviour of Self-Excited Induction Generator, which does not require rigorous modelling as required in conventional techniques. Proposed Artificial Neural Network (ANN) model has been implemented to predict the effect of speed, capacitance and load on generated voltage and frequency of SEIG. Experimental data is used for the training of ANN. Results obtained from the trained ANN are found to be in close agreement with the experimental results.

Keywords: Self-Excited Induction Generator, Artificial Neural Networks.

1. INTRODUCTION

Among renewable energy sources, wind energy conversion scheme is most promising and cost effective. Due to zero fuel cost and environmentally clean, electric power generation from wind farms is increasing in an amazing way. Wind powered systems have been widely used since tenth century for water pumping, grinding grains and other low power applications. In 1931, the Russians built a large windmill with a 100 ft diameter blade, but it had very low conversion efficiency [1].

Due to number of advantages of induction generators such as simple & rugged construction, low cost, absence of DC exciter etc., these have been found most suitable for wind energy conversion schemes. Induction generators can operate in two modes i.e. Grid Connected Operation and Isolated Induction Generator Operation. Grid connected operation is feasible when normal AC supply grid is available near the site. Induction machine connected to the grid operates as externally excited induction generator, while taking the excitation current from the grid, for which the operating speed of the machine must be greater than the synchronous speed. The output voltage and frequency does not change with loading conditions but active power generated by the machine is a function of slip. Induction machine connected across the capacitor bank when driven by the prime mover within the limits of lower and higher cut-off speeds operates as self excited induction generator. Under these conditions the capacitor bank meets the total reactive power requirements of the machine and load. Active power generated by the rotor is delivered to the load through stator.

This concept of self-excitation of induction machine emerged, for the first time in 1935, when Basset and Potter reported that the induction machine can be operated as an induction generator in isolated mode by using external capacitor [2]. Wagner (1939) gave an approximate method of analysis of self-excited induction generator by separating the real and reactive parts of the circuit [3]. The use of series capacitor for the analysis was also reported by Wagner (1941) to improve voltage across the load and presented systematic analysis of SEIG [4].

Recent advancements in Power Electronics have made it possible to regulate the SEIG in many ways, which has resulted in an increased interest in the use of induction generators for small scale power generation with wind power and low hydro heads [5]. Various researchers have used conventional techniques, which involve cumbersome mathematical procedures for steady state performance evaluation of self-excited induction generator [6-8]. Bhim studied the effect of variable speed operation employed in case of an isolated induction generator operation to feed frequency insensitive loads [9]. Sandhu and Jain suggested new equivalent circuit model for the analysis, which resulted in only quadratic equation for slip instead of fourth or higher order polynomial solutions to predict the behaviour of SEIG [10].

At present application of Artificial Intelligence techniques are gaining importance in the field of engineering. Artificial Neural Networks are one of the computational tools, which try to mimic the method of computation adopted by human brain and are bestowed with the features of human like

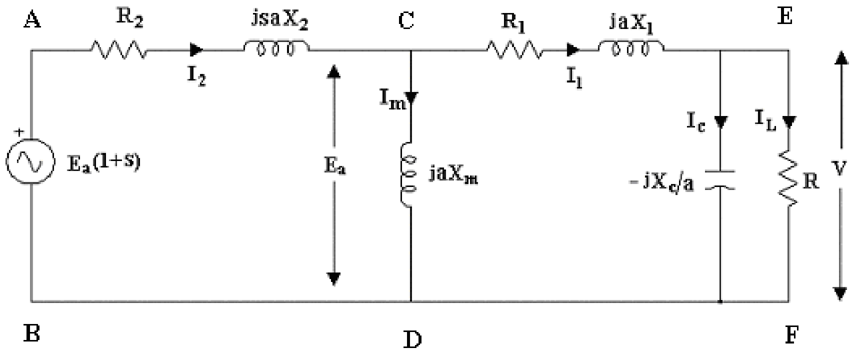

Figure1. Per Phase Equivalent Circuit of SEIG

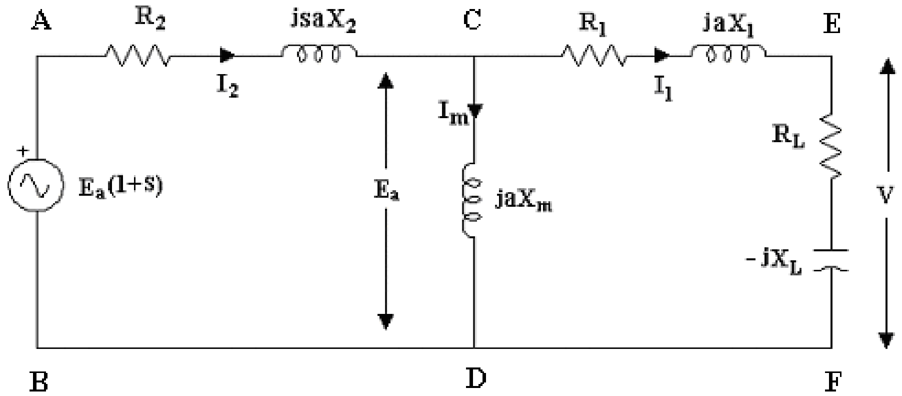

Figure 2. Per Phase Simplified Equivalent Circuit of SEIG

intelligence. Analysis using Artificial Neural Networks (ANNs) technique does not require rigorous modelling as required in conventional methods. The most commonly used neural network is the Multilayer Perceptron (MLP), a feed-forward network. The neural networks are trainable but these black-box models are able to identify a system through its input-output data, without having any knowledge of the physical insights of the system. From the literature survey carried out, it is clear that Artificial Neural Networks are being applied to study and analyze the behaviour of Electrical machines. Siva et al. used Artificial Neural Networks for estimation of System Bus Voltage in power system [11].

Goel and Bhanot developed Successive Over-Relaxation Resilient Back propagation (SOR-RPROP) algorithm, which is extremely fast in comparison to conventional backpropagation algorithm for training of ANNs [12]. Chaturvedi et al. used Error Backpropagation gradient descent learning algorithm for training the Neural Network Models for electric machines to map complicated functions [13]. Here, an attempt has been made to introduce ANNs for performance prediction of induction generators. Artificial Neural Networks have been used to evaluate the generated voltage and frequency of SEIG running at different speeds with different values of exciting capacitance and load.

2. STEADY STATE ANALYSIS OF SEIG

Equivalent circuit model has been used for steady state analysis of Self-Excited Induction Generator [10]. Figure 1 gives per phase equivalent circuit of SEIG, showing voltage generated by rotor as an active source.

Where;

R_1, X_1 = stator resistance and reactance.

R_2, X_2 = rotor resistance and reactance referred to stator.

R, X_c = load resistance and capacitive reactance.

X_m = saturated reactance of induction generator.

a = ratio of generated to rated frequency.

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

s = slip of machine.

E_1 = air gap voltage per phase at rated frequency.

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

$E_a(1+s)$ is the source voltage corresponding to mechanical power transformed to electrical power through rotor and V is the output voltage.

All quantities referred above are in per unit values.

Parallel combination of load resistance R and capacitive reactance X_c results into per phase series resistance R_L and reactance X_L. The values of R_L and X_L in terms of load resistance R and capacitive reactance X_C are given below:

$$R_L = RX_C^2 / (a^2R^2 + X_C^2)$$

$$X_L = aR^2X_C / (a^2R^2 + X_C^2)$$

From Figure 2 net impedance Z_L across EF becomes:

$$Z_L = R_L - j X_L$$

(-ve sign indicates capacitive effect)

Combining rotor impedance, net impedance across CF can be written as:

$$R_{1L} = R_1 + R_L$$

$$X_{1L} = aX_1 - X_L \qquad (X_L > aX_1)$$

Nodal analysis of the circuit in figure 2, seen from node C gives two equations by separating the real and imaginary components:

Real part:

$$\frac{R_{1L}}{(R_{1L}{}^2 + X_{1L}{}^2)} - \frac{sR_2}{(R_2{}^2 + s^2a^2X_2{}^2)} = 0 \qquad \ldots(1)$$

Imaginary part:

$$\frac{s^2aX_2}{\left(R_2{}^2 + s^2a^2X_2{}^2\right)} - \frac{X_{1L}}{(R_{1L}{}^2 + X_{1L}{}^2)} - \frac{1}{aX_m} = 0 \qquad \ldots(2)$$

Simplifying equation (1), the following quadratic equation in terms of slip is developed:

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

where;

$$A = a^2X_2{}^2R_{1L}$$

$$B = -R_2(R_{1L}{}^2 + X_{1L}{}^2)$$

$$C = R_2{}^2R_{1L}$$

Equation (1) & (2) result into evaluation of X_m.

$$Xm = \frac{-R_2(R^2{}_{1L} + X^2{}_{1L})}{(sa^2X_2R_{1L} + aR_2X_{1L})} \qquad \ldots(4)$$

The relation between a & b can be written as:

$$a = b/(1+s) \qquad \ldots(5)$$

Now, unknown values of magnetizing reactance 'X_m' and p.u frequency 'a' are obtained by solving equations 1 to 5. Further, computed value of X_m can be used to determine the air gap voltage 'E_a' using magnetizing characteristics of the machine [Appendix-I]. Computation of E_a for given value of operating speed 'b', exciting capacitance 'C' and load resistance 'R' lead to complete solution of equivalent circuit.

2. ARTIFICIAL NEURAL NETWORKS - THE BASICS

ANNs incorporate the two fundamental components of biological neural nets i.e. Neurons (nodes) and Synapses (weights). Neurons are arranged in different layers. The input layer, contains neurons equal to number of input variables and output layer contains the neurons equal to the number of output variables. The number of neurons in the hidden layer forms different structures and have different mapping capabilities. There is a need to choose an appropriate number of neurons in hidden layer so as to get the optimal performance from the neural network. Figure 3 (a) represents the arrangement of neurons and their inter-connections in different layers. Data is presented to input layer and then passed on to hidden layer. After processing, the data is passed on to output layer. In Feed-Forward Neural Networks (FFNNs) the information processing is unidirectional, parallel and distributed. The input to any neuron is processed through squashing function to give output between the limits 0 and 1 that is depicted from figures 3 (b) & (c). Output of any neuron is given as:

$g(a) = 1/ (1+ e^{-a})$, where 'a' is the sum of weighted output of the previous layer.

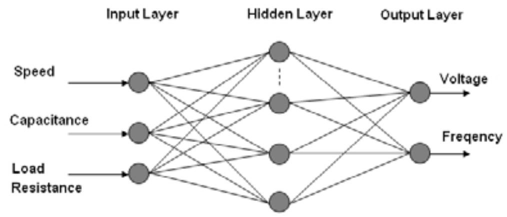

Fig 3(a) MLP Network Architecture

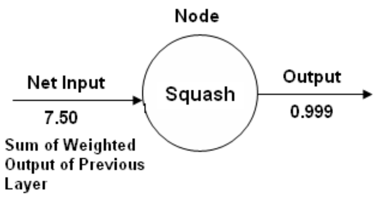

Fig 3(b) Input - Output of a node

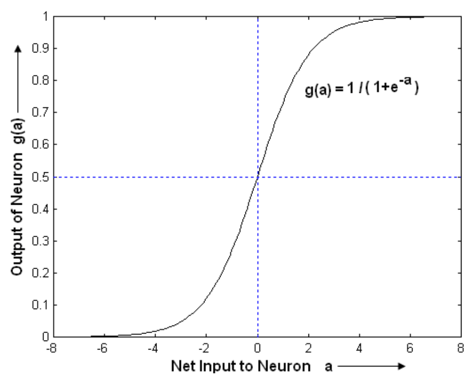

Fig 3(c) Squashing Function

4. SIMULATION DETAILS

The ANN model of SEIG was implemented using Multilayer Perceptron (MLP) network. It is known that ANNs with only one hidden layer can

Table 1. Range of Input Variables for Experimental Data.

Sr. No.	Experiment Set No.	Speed RPM From	Speed RPM To	Capacitance C (μF)	Load Resistance R (Ω)	No. of samples
01	Set #1	1430	1600	36	160	12
02	Set #2	1270	1450	51	160	12
03	Set #3	1400	1570	36	220	12
04	Set #4	1280	1420	51	220	12

approximate any function to any degree of accuracy provided it has sufficient number of neurons in the hidden layer. Therefore only one hidden layer has been used in the MLP network. The input layer has three neurons accounting for three inputs namely: speed of prime mover; b, load resistance; R and capacitance; C. The output layer has two neurons that account for the two outputs namely: terminal voltage; V and frequency; f. The hidden layer was chosen to have seven neurons, hence MLP architecture for ANN used is 3-7-2.

Test machine [Appendix-I] has been used to obtain experimental data for training purpose as well as for experimental verification of computed results obtained from trained ANN. The performance of SEIG at variable speed, exciting capacitance and with different loads was first evaluated experimentally to obtain four sets of input-output data required for training of ANN. Table 1 gives the details of each data set taken on test machine. The range of speed and value of terminal capacitance have been chosen to enable the machine to supply power to the connected load at rated voltage. The resistive load is not sensitive to change in frequency. Therefore, the two values of load resistance were chosen arbitrarily. Twelve experimental input-output observations have been taken for each set. Out of these, six samples from each set (i.e. a total of 24 samples) have been used for training the neural network. 24 samples (other than training samples), six from each set have been used to verify the results from the trained ANN model.

Successive Over-Relaxation Back Propagation (SORRPROP) training algorithm is used for training the ANN [12]. SORRPROP is modified version of RPROP [14] and makes use of successive over-relaxation principle to increase convergence speed of the network. The Sum Squared Error (SSE) goal has been set at 0.000075. The initial learning rate for training of the network is kept as 0.01 for both the hidden and the output layer.

Table 2 Set # 1 Comparison of Results

Capacitance C = 36 μF Load Resistance R = 160 Ω						
Speed RPM	Voltage (V)			Frequency (f)		
	Analytical	Expt.	ANN	Analytical	Expt.	ANN
1433	134.1368	134	134.46	47.1745	47.19	47.19
1467	158.3876	158	157.48	48.2894	48.30	48.30
1498	178.4280	176	177.81	49.3056	49.35	49.31
1516	188.0909	189	188.86	49.8955	49.92	49.89
1543	202.4747	203	203.87	50.7802	50.74	50.78
1596	230.3602	228	228.20	52.5161	52.54	52.54
SSE*	12.7368	-----	4.6131	0.0051	-----	0.0041

Table 3. Set # 2 Comparison of Results

Capacitance C = 51 μF Load Resistance R = 160 Ω						
Speed RPM	Voltage (V)			Frequency (f)		
	Analytical	Expt.	ANN	Analytical	Expt.	ANN
1280	163.8196	166	166.24	42.1136	42.17	42.15
1321	185.4419	187	186.66	43.4553	43.50	43.54
1353	199.2042	201	200.80	44.5020	44.67	44.64
1390	212.0390	215	215.16	45.7116	45.91	45.87
1440	229.2695	232	232.50	47.3451	47.40	47.43
1445	230.9866	234	233.88	47.5084	47.55	47.55
SSE*	49.0072	----	0.5058	0.1177	-----	0.0054

*SSE : Sum -Square Error with reference to experimental results

Table 4 Set # 3 Comparison of Results

Capacitance C = 36 μF Load Resistance R = 220 Ω						
Speed RPM	Voltage (V)			Frequency (f)		
	Analytical	Expt.	ANN	Analytical	Expt.	ANN
1403	129.7862	123	122.97	46.3343	47.04	47.04
1442	157.9313	154	153.71	47.6181	47.64	47.90
1467	174.5763	171	171.13	48.4409	48.28	48.37
1496	190.3046	188	186.79	49.3951	49.24	49.40
1540	213.8753	210	211.45	50.8424	50.78	50.80
1563	227.1258	224	223.79	51.6644	51.13	51.12
SSE*	104.3967	------	3.7234	0.8379	-----	0.1018

Table 5. Set # 4 Comparison of Results

Capacitance C = 51 μF Load Resistance R = 220 Ω						
Speed RPM	Voltage (V)			Frequency (f)		
	Analytical	Expt.	ANN	Analytical	Expt.	ANN
1285	175.9696	174	173.9	42.4105	42.43	42.43
1315	191.8326	187	187.36	43.3960	43.41	43.44
1350	204.1371	202	202.37	44.5452	44.50	44.59
1386	216.7150	216	216.93	45.7268	45.70	45.80
1406	223.6741	223	224.77	46.3829	46.41	46.49
1430	232.0025	237	236.92	47.1701	47.62	47.62
SSE*	57.7408	-----	4.3024	0.2065	-----	0.0254

*SSE : Sum -Square Error with reference to experimental results

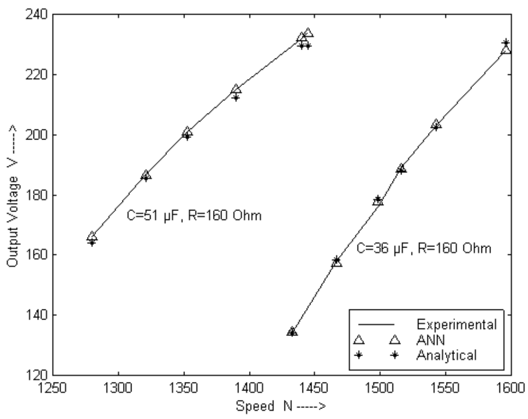

Figure 4 Voltage v/s Speed for Different Value of Capacitance & Load Resistance

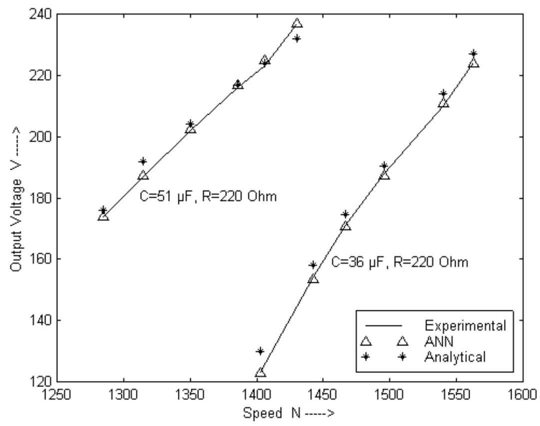

Figure 5 Voltage v/s Speed for Different Value of Capacitance & Load Resistance.

5. RESULTS AND DISCUSSION

Four sets of experiments were conducted on the test machine to obtain experimental data for verification of proposed ANN performance with given values of excitation capacitance, operating speed and load resistance.

Tables 2 to 5 give the comparison of results obtained from the trained ANN model, analytical method described in section II with experimental data. The experimental data for testing of trained ANN is different than the training data. The Sum-Square- Error obtained for analytical and ANN solutions with reference to experimental data is also included in the tables.

For first set of results (Table 2), it is observed that although the SSE value for frequency in case of analytical and ANN solutions do not differ much. But, SSE value with reference to experimental results for voltage obtained from conventional technique is very large (12.7368) compared to that for ANN solution (4.6131). For the 2nd set of test samples (Table 3), SSE of analytical analysis in case of voltage with reference to experimental results is about 50 times and that of frequency is 20 times as compared with the SSE of ANN solutions.

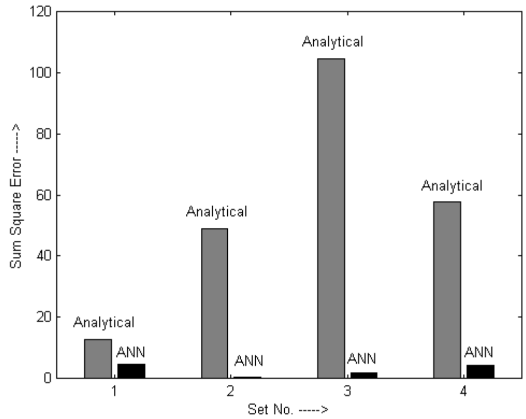

Figure 6. Sum-Square Error in Output Voltage with Reference to Experimental Results.

For 3rd set of test samples (Table 4), the SSE values obtained from analytical solution are observed to be 25 times & 8 times higher than that of ANN results for voltage and frequency respectively. Similar trends (Table 5) have been observed in the 4th set of testing samples.

A close agreement between experimental and ANN simulation results prove the validity of ANN modelling. Moreover, ANN model results are found to be far superior in comparison with conventional computational techniques. Further, ANN model of SEIG does not require any assumptions and complex mathematical computations unlike in conventional analytical techniques. It only needs experimental data for training. Nowadays, with the use of precision measuring instruments, large amount of experimental data can be obtained and therefore, accuracy of ANN model can be improved further by increasing the number of training samples.

Effect of speed on output voltage of SEIG with different values of capacitance and load resistance is shown in figures 4 and 5. It is established that higher value of capacitance lowers the speed requirements to generate rated voltage at particular load. But at lower speeds the output frequency decreases, thus capacitance and operating speed have interdependence to generate rated voltage and frequency. Further from figure 6, it is clear that SSE of ANN model with reference to experimental results is very small as compared to the SSE of analytical results. This establishes the superiority of ANN model over conventional analytical techniques.

6. CONCLUSIONS

Self–excited induction generators are found to be very useful for remote and windy areas in case terminal voltage and frequency are controllable. This can be achieved with prior estimation of performance of induction machine as generator. In this paper, ANN model has been implemented to predict the effect of speed, capacitance and load resistance on generated voltage and frequency of Self-Excited Induction Generator (SEIG). It is seen that the analysis carried out using ANN model is more accurate in comparison to conventional computational techniques. From the difference in SSE values of the ANN solution and the analytical method, it is concluded that ANN technique is superior in comparison to conventional analytical method. Further, ANN model of SEIG does not require any assumptions and complex mathematical computations. By increasing the number of training samples, the accuracy of ANN model can be further improved.

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Appendix - I

Machine Specifications:

3-Phase, 50 Hz, 2.2 KW/3.0 HP, 4-pole, 230 Volts, 8.6 Amp. Delta connected squirrel cage induction machine.

Machine Parameters:

$R_1 = 3.35\ \Omega$ $R_2 = 1.76\ \Omega$ $X_1 = 4.85\ \Omega$ $X_2 = 4.85\ \Omega$

Magnetization characteristics of machine for determination of air gap voltage:

$E_1 = 344.411 - 1.610\ X_m$	$X_m < 82.292$
$E_1 = 465.120 - 3.077\ X_m$	$95.569 > X_m \geq 82.292$
$E_1 = 579.897 - 4.278\ X_m$	$108.00 > X_m \geq 95.569$
$E_1 = 0$	$X_m > 108.00$

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