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Determination of Magnetising Reactance and Frequency of Self-Excited Induction Generator using ANN Model

[1]Raja Singh Khela and [2]K.S. Sandhu

[1]Department of Electrical Engg, Sri Sai Group of Institutes,
Badhani–Pathankot, Punjab, India
E-mail: rskhela@rediffmail.com
[2]Department of Electrical Engg,
National Institute of Technology, Kurukshetra, Haryana, India

Abstract

To evaluate the overall performance of Self-excited Induction generator (SEIG), prior information of three unknown variables i.e. per unit value of saturated magnetizing reactance 'X_m', generated frequency 'a' and air-gap voltage 'E_1' at rated frequency are essentially required. Analytical methods along with the laboratory test on machine are the only alternative to determine these unknown variables. Nonexistence of direct mathematical relationship of these variables and their dependence on machine parameters, load admittance, speed and terminal capacitance has forced the researchers to evolve new computational techniques. Artificial Neural Networks (ANNs) are the latest computational tools that are widely used for function approximation of systems having non-linear characteristics. ANNs have the capability to model the behaviour of the system to any degree of accuracy. Artificial Neural Networks (ANNs) are very useful tool for solution of such complex problems that do not require any a priori knowledge of the relationship of input and its output. In this paper, an attempt is made to use artificial neural networks to determine the saturated magnetizing reactance and generated frequency of SEIG with varying terminal conditions of load and speed.

Introduction

The utility of Self-Excited Induction Generator (SEIG) in power system networks had started gaining importance when it was found difficult to wheel out power through transmission and distribution lines in remote areas due to difficult geographical conditions. With the passage of time and use of non-conventional energy sources particularly wind energy, the operation of SEIG emerged as a cost-effective alternative, where it was not economical to connect the consumer through electric lines. This has led to the intensive investigations pertaining to the performance of self-excited induction generator by various researchers. The concept of self-excitation of induction machine emerged, for the first time in 1935, when Basset and Potter [1] reported that the induction machine can be operated as an induction generator in isolated mode by using external capacitors. Wagner [2] in 1939 gave an approximate method of analysis of self-excited induction generator by separating the real and reactive parts of the circuit. The use of series capacitor for the analysis was also reported by Wagner [3] in 1941 to improve voltage across the load and presented systematic analysis of SEIG. Since then, different researchers have made various attempts in this field. Barkle and Fergusen [4] in 1954 proposed the analysis of SEIG using modified synchronous machine transient theory.

Murthy et. al. [5] presented Newton Raphson (NR) method to identify the saturated magnetizing reactance and generated frequency of self-excited induction generator for given capacitance, speed and load. Malik and Haque [6] predicted steady state performance of an isolated self -excited induction generator feeding balanced R-L load considering core losses for accurate analysis, which was neglected earlier in the analysis by some of the researchers. Chan [7] used MACSYMA (MAC's Symbolic Manipulation) for the analysis of SEIG based on nodal admittance method. Bhim [8] studied the effect of variable speed operation employed in case of an isolated induction generator operation to feed frequency in-sensitive loads. Sandhu and Jain [9-10] suggested new equivalent circuit model for the analysis of self -excited induction generator, which resulted in only quadratic equation for slip instead of fourth or higher order polynomial solutions to predict the behaviour of machine.

From the literature survey carried out, it is clear that techniques like Artificial Neural Networks are being applied to study and analyze the behaviour of electrical machines and other power system networks. Chaturvedi et. al. [11] used back propagation gradient descent learning algorithm for training the Flexible Neural Network (FNN) models for electric machines to map complicated functions. Krüger et. al. [12] studied two types of artificial Neural Networks i.e. Multilayer Perceptron (MLP) Network and the Radial Basis Function (RBF) Network, which were used to model the process dynamics. Resilient Back propagation Technique, Levenberg-Marquardt (LM) and Successive Over-Relaxation Resilient Back propagation, (SORRPROP) algorithms is suggested by some of the researchers to enhance the training capability of neural networks [13-14]. Lucia and Petrecca [15] established the possibility to use neural networks for load torque monitoring of an induction motor. Velpula and Das [16] used artificial neural networks technique for estimation of system bus voltage in power systems. The neural networks are trainable but the 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. Neural Network can be configured to solve a number of difficult and complex problems. ANNs find a wide variety of applications in diverse areas including functional approximation, nonlinear system identification and control [17-19].

Self–Excited Induction Generator and its ANN Model

Induction machine when driven with prime mover can be made to operate as an isolated induction generator by supplying the necessary exciting or magnetizing current from capacitors connected across the stator terminals of the machine. Excitation to the induction machine when supplied by the capacitor bank makes the operation of machine as self-excited induction generator. Per phase equivalent circuit of SEIG is shown in Figure 1.

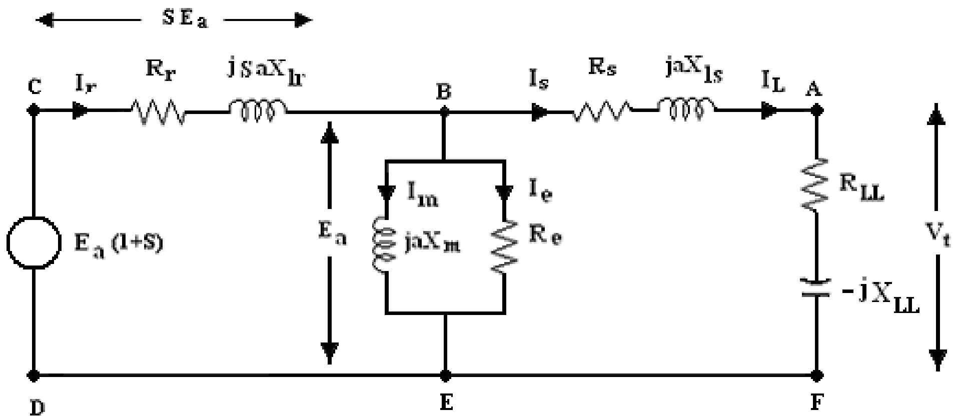

Figure 1: Per Phase Simplified Equivalent Circuit of Self-Excited Induction Generator.

Artificial Neural Networks (ANNs) are the latest computational tools that are widely used for function approximation of systems having non-linear characteristics. ANNs have the capability to model the behaviour of the system to any degree of accuracy. Mechanical disorder of machine components due to sudden disturbances, aging and abnormal use causes change in machine parameters and magnetizing behaviour of induction machinery. While using conventional techniques for the analysis of self-excited induction generator, the effect of such changes are not considered. But the ANN model can incorporate such changes. Apart from this ANNs have the capability to learn and adapt for any environmental changes. ANN model of the system can be given on-line training to adapt to any parametric changes in the system inputs, which automatically affects the corresponding changes in the outputs. In this work, selection of range of input-output variables for generation of training samples, training procedure and implementation of trained ANN for evaluation of unknown variables are discussed in detail.

Selection of Range of Input Variables for ANN Model

Though ANN model of self-excited induction generator need not to have prior knowledge of mathematical relationship of its inputs with the corresponding outputs but the upper and the lower limits of the input - output variables have to be chosen carefully so that the model can give adequate performance when applied on systems having inputs within the range that should generally match with real life application of the system. To ascertain an acceptable range of machine parameters to be used for ANN model, data of different induction motors is recorded that was obtained during testing of motors which were referred to G.Z.S. College of Engg. & Tech. Bathinda by the enforcement wing of Punjab State Electricity Board to establish the HP of induction motors of consumers. The machines specifications and their parameters recorded during testing is given in Table 1. From the information recorded, it is observed that the value of stator and rotor resistance varies from 0.015 to 0.065 per unit approximately, whereas rotor and stator leakage reactance varies between 0.072 to 0.147 per unit.

Table 1: Specifications and Machine Parameters (measured / recorded) of Induction Motors Referred by Punjab State Electricity Board for Testing at GZS CET, Bathinda.

Machine HP	V_{bas} Volt	I_{base} Amp	Z_{base} ohm	R_s pu	R_r pu	X_{ls} pu	X_{lr} pu	R_e pu	X_{mu} Pu
23.08	415	17.49	23.723	0.035	0.032	0.072	0.072	45.875	2.350
21.15	415	17.356	23.910	0.040	0.052	0.074	0.074	53.541	1.919
15.34	415	14.202	29.220	0.055	0.064	0.141	0.141	34.690	1.830
44.14	440	40.833	10.775	0.065	0.064	0.103	0.103	17.502	1.567
101.62	435	73.236	5.9396	0.015	0.040	0.141	0.141	15.948	4.930
62.14	425	47.143	9.0150	0.031	0.035	0.147	0.147	13.252	4.350
77.24	433	63.331	6.8371	0.021	0.045	0.113	0.113	41.673	1.842
80.17	433	58.202	7.4395	0.017	0.031	0.107	0.107	43.391	2.591
75.07	440	56.124	7.8397	0.020	0.016	0.114	0.114	85.445	2.045

Table 2: Range of Machine Parameters and Terminal Variables for Training of ANN Model of SEIG.

Machine Parameters and Range		**Terminal Variables and Range**	
Parameters	**Range (pu value)**	**Parameters**	**Range (pu value)**
Stator Resistance (R_s)	0.02 -0.10	Excitation Capacitance (C)	0.60 – 1.20
Rotor Resistance (R_r)	0.02 -0.10	Load Admittance (Y_L)	0.01 – 1.00
Stator Reactance (X_{ls})	0.04 -0.15	Load Power Factor (Pf)	0.85 – 1.00
Rotor Reactance (X_{lr})	0.04 -0.15	Operating Speed (b)	0.90 – 1.10
Core- loss Branch Resistance (R_e)	25 - 60		

Based on these investigations and keeping in view the real life situations, the range for all the input variables required for training of ANN model of SEIG are chosen which are given in Table 2 and ANN model of SEIG is shown in Figure 2.

Generation of Input Output Data Samples and Training Procedure

For training of ANNs, the input-output data samples are obtained either from experimentation or from past data records or by using any mathematical technique. In this work the output data samples are obtained by using the analytical technique with randomly chosen input variables within the range specified above. For training the neural network, four thousand input-output data samples are taken covering the full range of input variables as described earlier. The ANN structure with nine neurons in the input layer accounting for input variables and two neurons representing the output variables with single hidden layer is proposed. Neural network having ANN structure [9 - 12 - 2] as shown in Fig 2 is proposed for determination of two unknown variables i.e. pu value of magnetizing reactance and generated frequency.

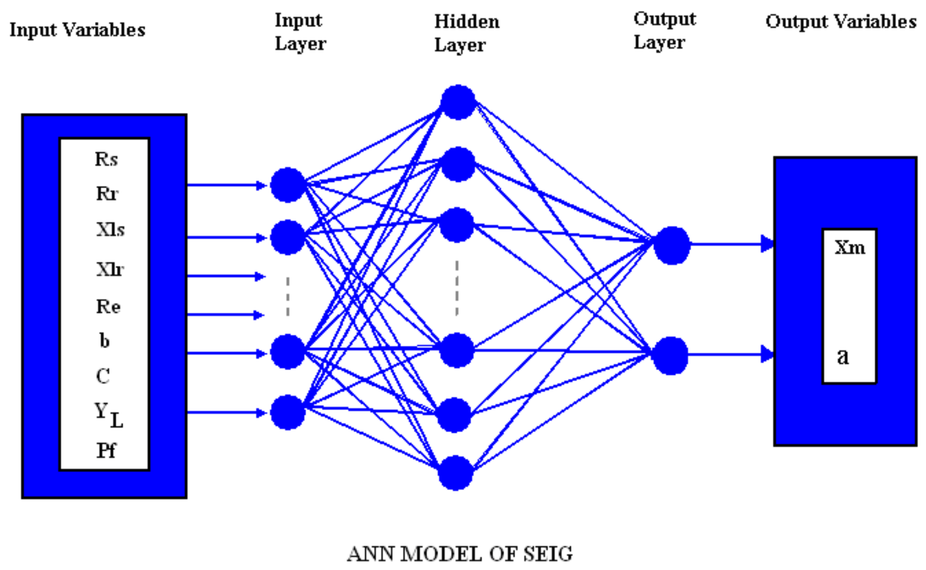

Figure 2: ANN Model of SEIG to Determine Mag. Reactance and Frequency.

Before presenting the data to the neural network, input-output data samples are scaled or normalized to improve the mapping capability of the neural nets. Though input-output data can be scaled between any lower and upper limits, but in this work input-output data sample are scaled between lower and higher limits of 0.10 and 0.90 respectively. To scale any vector within the limits of 0.10 and 0.90 the following expressions are used:

In any system if $Y = f(X)$ for any input value of X, the scaled value X_{scaled} and Y_{scaled} are given in equation (1) and (2)

$$X_{scaled} = 0.10 + \left(\frac{X - X_{min}}{X_{max} - X_{min}} \right) 0.80 \quad ---(1)$$

$$Y_{scaled} = 0.10 + \left(\frac{Y - Y_{min}}{Y_{max} - Y_{min}} \right) 0.80 \quad ---(2)$$

where

X_{min} = Minimum value of vector X *for* input data samples.

X_{max} = Maximum value of vector X *for* input data samples.

Y_{min} = Minimum value of vector Y *for* output data samples.

Y_{max} = Maximum value of vector Y *for* output data samples.

Training Parameters and Validation of ANN Model

Using artificial neural network tools in MATLAB, the neural network is trained using Levenberg–Marquardt (LM) training algorithm. The sum-square error (SSE) goal is set at 0.0075. Initially the network is trained with randomly chosen weights and biases. Leaning rate for the hidden and output layer is initially set at 0.01. The training procedure is repeated till the minimum sum square error goal is achieved and the trained weights and biases are saved for implementation of ANN model. The performance of the trained ANN is then tested with validation data samples (10% to 15 % of training samples) which are other than training samples. In case the sufficient function approximation accuracy in terms of sum-squared error on validation data samples is not achieved then network can be further trained by setting a new error goal otherwise trained ANN is implemented for execution of testing data samples. In this case the minimum error goal is achieved in 5741 training epochs and sufficient accuracy in output results on randomly chosen validation data samples is observed.

Implementation of ANN Model of SEIG (Resistive Loading)

The trained ANN model of SEIG is implemented to evaluate the magnetizing reactance and generated frequency of self-excited induction generator under the following operating conditions:

- Variable Load Operation
- Variable Speed Operation

- **Variable Load Operation of SEIG**

  For variable load operation of machine, the load is varied in eight steps keeping the speed and excitation capacitance constant. In first case the trained ANN model is tested for variable load operation with excitation capacitance of 27.57

micro farad and 1485 Rpm speed. Similarly the output of ANN model is obtained with terminal capacitance of 23.58 micro farads and speed of 1570 Rpm. The results obtained from ANN model are recorded in Table 3(a) & 3(b) for comparison with analytical and experimental data. The variation of generated frequency and magnetizing reactance of SEIG with variable load is shown in Figure 3 & 4. Thus air gap voltage (E_a) for evaluating the overall performance of the SEIG can be determined from the magnetizing characteristics of machine given in Appendix – I.

Table 3(a): Results of ANN Model of SEIG for Variable Load Operation.

Speed = 1485 Rpm Capacitance = 27.57 micro farad					
Load Admittance (pu)	**Magnetizing Reactance (pu)**		**Generated Frequency (pu)**		
	Analytical Model	**ANN Model**	**Analytical Model**	**ANN Model**	**Experimental**
0.2250	1.2323	1.2276	0.9757	0.9755	0.9762
0.4131	1.3401	1.3367	0.9671	0.9672	0.9680
0.5384	1.4342	1.4316	0.9616	0.9618	0.9630
0.5808	1.4710	1.4692	0.9598	0.9599	0.9614
0.6389	1.5261	1.5258	0.9573	0.9575	0.9588
0.8191	1.7404	1.7470	0.9499	0.9502	0.9516
0.8712	1.8179	1.8250	0.9478	0.9482	0.9494
0.9489	1.9501	1.9527	0.9448	0.9453	0.9462

Table 3(b): Results of ANN Model of SEIG for Variable Load Operation.

Speed = 1570 Rpm Capacitance = 23.58 micro farad					
Load Admittance (pu)	**Magnetizing Reactance (pu)**		**Generated Frequency (pu)**		
	Analytical Model	**ANN Model**	**Analytical Model**	**ANN Model**	**Experimental**
0.2250	1.2948	1.2849	1.0320	1.0321	1.0330
0.4131	1.4162	1.4112	1.0230	1.0229	1.0240
0.5384	1.5252	1.5227	1.0172	1.0170	1.0182
0.5808	1.5684	1.5671	1.0152	1.0150	1.0164
0.6389	1.6339	1.6343	1.0126	1.0124	1.0142
0.8191	1.8956	1.8993	1.0048	1.0045	1.0064
0.8712	1.9930	1.9947	1.0026	1.0024	1.0038
0.9489	2.1627	2.1559	0.9994	0.9993	1.0012

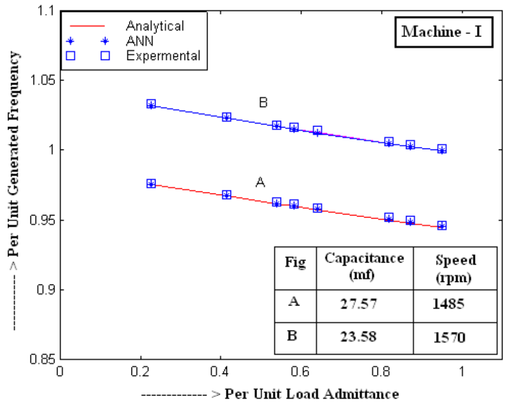

Figure 3: Effect of Load Admittance on Generated Frequency of SEIG.

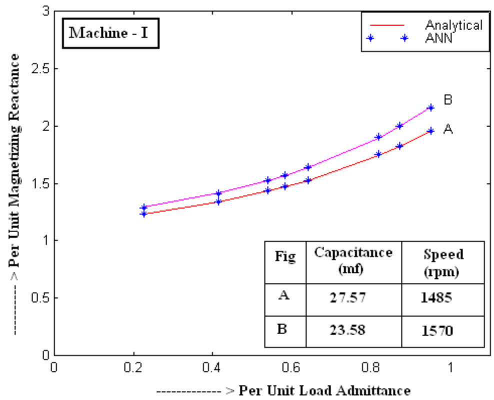

Figure 4: Effect of Load Admittance on Magnetizing Reactance of SEIG.

- **Variable Speed Operation of SEIG**
  The trained ANN model of SEIG is implemented for machine operation with 22.11 micro farad excitation capacitance and 232 ohm resistive load by varying the speed. Another set of outputs of ANN model is obtained with 26.45 microfarad capacitance and 110 ohm resistive load. The results obtained from ANN model are recorded in Table 4(a) and 4(b) for comparative study relating to performance of SEIG.

The graphical presentation of results of ANN model, analytical solution and experimental data with varying speed is given in Fig. 5 & 6. From the results obtained from ANN model, it is clear that magnetizing reactance increases with increase in load admittance and decreases with the increase in speed which implies that air-gap voltage will also increases with increase in speed. Thus air gap voltage (E_a) for evaluating the overall performance of the SEIG can be determined from the magnetizing characteristics of machine given in Appendix – I. The closeness of results thus validates the applicability of the proposed ANN model.

Table 4(a): Results of ANN Model of SEIG for Variable Speed Operation.

Capacitance = 22.11 micro farad Load Resistance = 232 ohms					
Speed (pu)	**Magnetizing Reactance (pu)**		**Generated Frequency (pu)**		
	Analytical Model	**ANN Model**	**Analytical Model**	**ANN Model**	**Experimental**
0.9233	1.9697	1.9693	0.9036	0.9035	0.9044
0.9307	1.9378	1.9382	0.9107	0.9106	0.9116
0.9533	1.8441	1.8457	0.9327	0.9326	0.9336
0.9900	1.7058	1.7065	0.9683	0.9682	0.9696
1.0140	1.6233	1.6221	0.9916	0.9916	0.9926
1.0467	1.5201	1.5158	1.0233	1.0232	1.0244
1.0713	1.4484	1.4426	1.0472	1.0470	1.0482
1.0967	1.3797	1.3747	1.0718	1.0710	1.0726

Table 4(b): Results of ANN Model of SEIG for Variable Speed Operation.

Capacitance = 26.45 micro farad Load Resistance = 110 ohms					
Speed (pu)	**Magnetizing Reactance (pu)**		**Generated Frequency (pu)**		
	Analytical Model	**ANN Model**	**Analytical Model**	**ANN Model**	**Experimental**
0.9233	2.1966	2.1975	0.8851	0.8850	0.8858
0.9307	2.1627	2.1643	0.8921	0.8921	0.8928
0.9533	2.0628	2.0665	0.9135	0.9139	0.9144
0.9900	1.9156	1.9215	0.9482	0.9485	0.9488
1.0140	1.8280	1.8345	0.9708	0.9709	0.9716
1.0467	1.7184	1.7253	1.0016	1.0015	1.0026
1.0713	1.6423	1.6500	1.0248	1.0249	1.0260
1.0967	1.5696	1.5794	1.0486	1.0494	1.0496

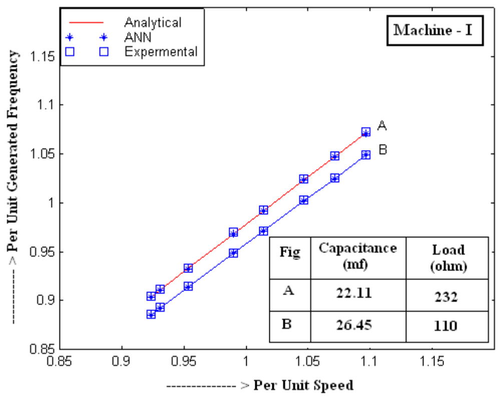

Figure 5: Effect of Speed on Generated Frequency of SEIG.

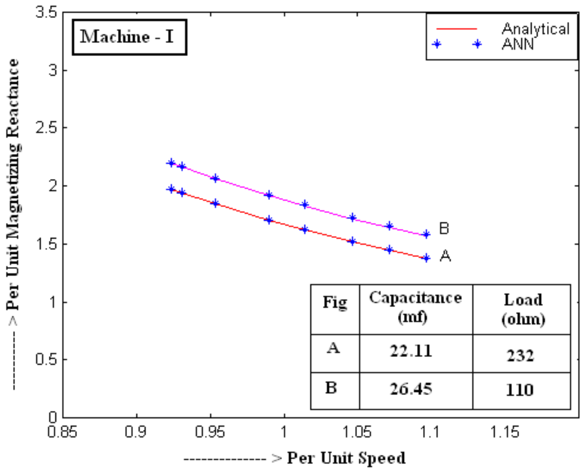

Figure 6: Effect of Speed on Magnetizing Reactance of SEIG.

Conclusions

In this work, Artificial Neural Networks is implemented to model the behaviour of self-excited induction generator. The ANN model is trained with randomly chosen input-output samples which cover the full range of machine parameters and terminal variables mentioned in Table 2. Though ANN model is trained for specific number of input sample but it is capable of determining the two un-known variables for INFINITE set of input variables. The ANN model is just a black box and is implemented to determine magnetising reactance and generated frequency of self-excited induction generator under varying conditions of load and speed. The deviations of results obtained from the proposed ANN model and conventional techniques are recorded in Table 5 and 6. The results obtained are quite encouraging and smaller values of deviations confirm that ANN model is fully capable of mapping the behaviour of machine under varying situations. From the results it is clear that the artificial neural network technique can be successfully implemented for the performance evaluation of self-excited induction generator. The closeness of the simulated results of ‘ANN Model’ with that of analytical and experimental results on the test machines confirms the validity of the proposed modelling using ANN.

Table 5: Deviations of Results of ANN Model of SEIG for Evaluation of Magnetising Reactance with Varying Terminal Conditions

Error	Variable Load Operation	Variable Speed Operation
Sum Square Error	0.0023	0.0017
Minimum error	0.0046	0.0007
Maximum error	0.0196	0.0262
Mean error	0.0131	0.0095
Std. Deviation	0.0044	0.0075

Table 6: Deviations of Results of ANN Model of SEIG for Evaluation of Generated Frequency with Varying Terminal Conditions.

Number of testing samples = 08		
Error	**Variable Load Operation**	**Variable Speed Operation**
SSE	1.310×10^{-06}	2.502×10^{-06}
Minimum error	7.631×10^{-05}	1.843×10^{-05}
Maximum error	4.183×10^{-04}	8.018×10^{-04}
Mean error	3.084×10^{-04}	3.682×10^{-04}
Std. Deviation	1.076×10^{-04}	2.766×10^{-04}

Appendix – I

a. Machine Specifications

$HP = 5.0$ $\quad P = 4$ $\quad V_{base} = 415\,Volts$

$P_{base} = V_{base} I_{base}$ $\quad N_{base} = 1500\ RPM$ $\quad I_{base} = 4.33\,Amp$

$F_{base} = 50\ Hz$ $\quad C_{base} = 33.21\,\mu F$ $\quad Z_{base} = 95.84\ \Omega$

b. Machine parameters in ohms

$R_s = 5.76\ \Omega$ $\quad R_r = 4.19\ \Omega$

$X_{ls} = 9.37\ \Omega$ $\quad X_{lr} = 9.37\ \Omega$

c. Magnetizing characteristics of machine:

$X_m < 2.6930$ $\quad E_a = 1.3818 - 0.2117 X_m$

$X_m < 2.8386\ \&\ X_m >= 2.6930$ $\quad E_a = 2.1697 - 0.5057 X_m$

$X_m < 2.9716\ \&\ X_m >= 2.8386$ $\quad E_a = 3.8732 - 1.1057 X_m$

$X_m > 2.9716$ $\quad E_a = 0$

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