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Identification of Optimal ANN Structure for Analysis of Self-Excited Induction Generator

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Abstract

The versatile features like universal function approximation ability to model non-linear and complex systems, learning and fault tolerance have resulted in widespread applications of Artificial Neural Networks (ANN) in diverse fields. The universal function approximation ability of ANNs depends upon the number of neurons in its hidden layer. There is no standard algorithm to determine the optimal number of hidden layer neurons. Small number of hidden neurons compromise with approximation ability of the network. On the other hand, large numbers of hidden layer neurons make the network more complex and increase training and execution times. In this paper, an attempt has been made to evolve a strategy for identifying the optimal number of hidden layer neurons based on Optimality Factor (OPF) obtained by varying the ratio of Error Weight and Network Complexity Weight. On the basis of per unit acceptability of network, optimal ANN structure is identified. Further, the evolved optimal ANN structure is used for performance analysis of Self-Excited Induction Generator (SEIG) with varying terminal conditions. The closeness of results with the experimental data validates the optimal ANN structure and its applicability to model the behaviour of SEIG.

Keywords: Artificial Neural Networks, Optimal ANN Strucure, Optimality Factor and Self-Excited Induction Generator.

Introduction

The growth of the industrial sector has resulted in a phenomenal increase in the demand for power. The power generation could not be stepped up correspondingly due to constraints in the availability of fossil fuels. Hence, the gap between demand and supply of power is increasing. Non-conventional sources of power generation offer a long-term solution to meet the power requirements. Wind, solar, biomass, mini-hydro power, geothermal and tidal waves cover the spectrum of the known renewable energy sources. Wind Energy has enormous potential in nature and the study confirms that the SEIG, Reluctance Generator and Permanent-Magnet Generator have emerged as suitable candidates for utilizing wind energy [1] in isolated and remote areas, where power distribution is not possible by conventional means of transmission and distribution.

Analysis of SEIG can be classified into two major groups: the first that deals with various aspects for steady-state operation and the other deals with the transient behaviour of the generator under different operating conditions. In the past, analysis of SEIG has been carried by analytical techniques based on loop impedance or nodal admittance method that involves solution of higher order polynomial in terms of frequency and magnetizing reactance to predict machine behaviour with varying terminal conditions [2-4]. Sandhu and Jain have developed a simple equivalent circuit model with voltage source that resulted in quadratic equation for slip instead of fourth or higher order polynomial solutions to evaluate generated frequency and magnetizing reactance of SEIG [5]. Thus, computational effort is reduced to the extent that calculations for the analysis can be carried on scientific calculator.

The Induction machine does not have the ability to control voltage, frequency and reactive power as is exhibited in synchronous generators. The generated frequency, voltage and output power of the SEIG depend upon prime mover speed, exciting capacitance and load, apart from the parameters of machine. Self-excited induction generator also suffers from inherent poor voltage regulation due to the difference between the VARs supplied by the shunt capacitors and the VARs required by the load and machine. The poor voltage regulation of SEIG results in reduction of loading capacity and under utilization. However, it can be improved by the use of voltage regulators based on fully controlled converter [6]. Singh et al. [7] have given an algorithm for calculating the number of capacitor steps to load the machine to its rated capacity while maintaining the load voltage within the specified upper and lower limit. Approximate analysis for long shunt SEIG has been used to calculate the value of shunt and series capacitors from the magnetizing characteristic and compounding effect of series capacitance is shown by graphical interpolation [8].

In modern times the main thrust of research is oriented towards applying artificial intelligence techniques in various scientific and industrial applications. Expert systems are one of the solution techniques more frequently adopted. Wollenberg suggested its use for alarm treatment [9]. Its main drawbacks are the incapacity of generalization and the difficulty of validating and maintaining large rule bases. Nowadays, new AI techniques like Artificial Neural Networks, Fuzzy logic and Genetic Algorithms are finding increased applications in the field of power system operation, protection, control, load forecasting and fault diagnosis etc. ANNs have an ability to learn, perceive and compute like human brain. These have the capacity to store knowledge about the problem domain and belong to the category of computationally intelligent systems. Hierarchical nets are proposed to reduce the dimension of the neural network, its computational effort, and training time [10]. 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]. This paper deals with the identification of optimal neural network and its implementation for steady state analysis of SEIG.

Conventional Technique for Performance Analysis Of SEIG

The Induction machine connected to infinite bus and driven with the external prime mover at speed higher than synchronous speed corresponding to the grid frequency has the capability to generate active power. In this mode of operation of machine as generator, the power bus supplies the magnetizing current to meet reactive power requirements. The voltage and frequency of the machine are not affected by the speed or the slip of machine. But, active power generated is a function of slip, which is always negative in this case. Excitation to the induction machine when supplied by the capacitor bank makes the operation of machine as self-excited induction generator. The output power, voltage and frequency of SEIG are a function of speed, exciting capacitance, load and parameters of the machine. The steady-state equivalent circuit of SEIG with load impedance is shown in Fig. 1.

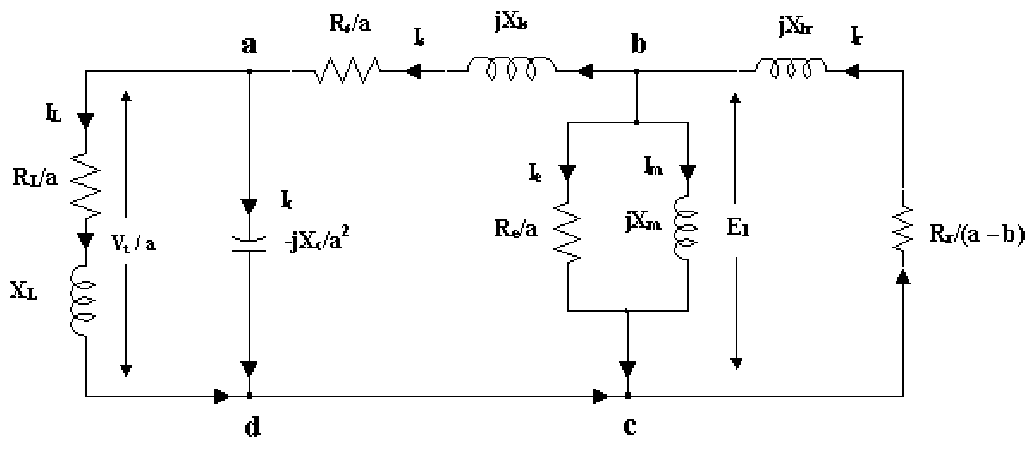

Figure 1: Equivalent circuit of self- excited induction generator.

Nomenclature for machine parameters and other variables

R_s, R_r, R_e	per phase stator, rotor and core loss branch resistance referred to stator
X_{ls}, X_{lr}	per phase stator and rotor leakage reactance referred to stator
X_m, X_c	per phase magnetizing and exciting capacitive reactance

R_L , X_L	per phase load resistance and reactance
b, a	speed and generated frequency
I_s, I_r, I_L	per phase stator, rotor and load current
E_1, V_t	per phase air gap voltage and terminal voltage at rated frequency.
P_o	3-phase output power.

Values referred above are in per unit and reactance values are w.r.t. base frequency f_{base} .

Branch impedance is obtained as under referring to equivalent circuit of Fig. 1.

$$Z_{ab} = \left(R_s / a + jX_{ls}\right)$$

$$Z_{ad} = \frac{\dfrac{-jX_c}{a^2}\left(R_L / a + jX_L\right)}{\left(R_L / a + jX_L\right) - \dfrac{jX_c}{a^2}}$$

$$Z_{bc} = \frac{(R_e / a // jX_m)\ \left(\dfrac{R_r}{a-b} + jX_{lr}\right)}{(R_e / a // jX_m) + \left(\dfrac{R_r}{a-b} + jX_{lr}\right)}$$

$$Z_s = Z_{ab} + Z_{ad} + Z_{bc}$$

The equivalent circuit results into a single loop equation:

$$I_s Z_s = 0 \tag{1}$$

For successful voltage build up;

$$I_s \neq 0 \text{ and hence } Z_s = 0 \tag{2}$$

By separating the real and imaginary components of equation (2) and putting each equation equal to zero, we get two non-linear simultaneous equations with magnetizing reactance X_m and generated frequency 'a' as unknown variables:

$$\begin{aligned} F_o(X_m, a) = {} & A_1 X_m a^5 + A_2 X_m a^4 + (A_3 X_m + A_4) a^3 \\ & + (A_5 X_m + A_6) a^2 + (A_7 X_m + A_8) a \\ & + A_9 X_m + A_{10} = 0 \end{aligned} \tag{3}$$

$$\begin{aligned} G_O(X_m, a) = {} & \left(B_1 X_m + B_2\right) a^4 + \left(B_3 X_m + B_4\right) a^3 \\ & + \left(B_5 X_m + B_6\right) a^2 + \left(B_7 X_m + B_8\right) a + B_9 = 0 \end{aligned} \tag{4}$$

A(s) and B(s) are the polynomial coefficients in terms of machine parameters and other variables i.e. capacitive reactance X_c , Speed b , load resistance R_L and reactance X_L and core loss branch resistance R_e **.**

The equations (3) and (4) are solved by Newton-Raphson method for two variables i.e. per unit magnetising reactance 'X_m' and per unit frequency 'a'. It involves tedious computer programming. The magnetizing characteristics of machine are determined experimentally by running the machine at synchronous speed corresponding to rated frequency. The expression for air gap voltage 'E_1' in terms of magnetizing reactance 'X_m' is given below:

Magnetizing characteristics of machine

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

With known values of magnetizing reactance 'X_m', frequency 'a' and air gap voltage 'E_1' the performance of machine can be determined for any terminal conditions by solving the equivalent circuit of SEIG.

Artificial Neural Networks

An artificial neural network is an information-processing paradigm that is inspired by the way biological nervous systems such as the brain process information. The key element of this paradigm is the neurons. 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, such as pattern recognition or data classification, through a learning process. Learning in ANNs involves adjustments to the synaptic interconnection weights that exist between the neurons.

The neurons in ANNs are grouped into layers. The input layer neurons receive input to form the external environment. The output layer neurons communicate the output of the system to the user or external environment. The layers of neurons between these two layers are called hidden layers. A simple structure of Multi-Layer Perceptron (MLP), an artificial neural network with one hidden layer is shown in Fig. 2. When the input layer receives the input, its neurons produce output; this becomes input to the next layer of the system. The process continues until a certain conditions are satisfied or until the output layer is invoked and fires their output to the external environment. There is no set algorithm to determine the optimal number of hidden layer neurons or the number of hidden layers. Single hidden layer is sufficient to approximate any function to any degree of accuracy. Therefore, in this paper, it is proposed to use single hidden layer ANN only.

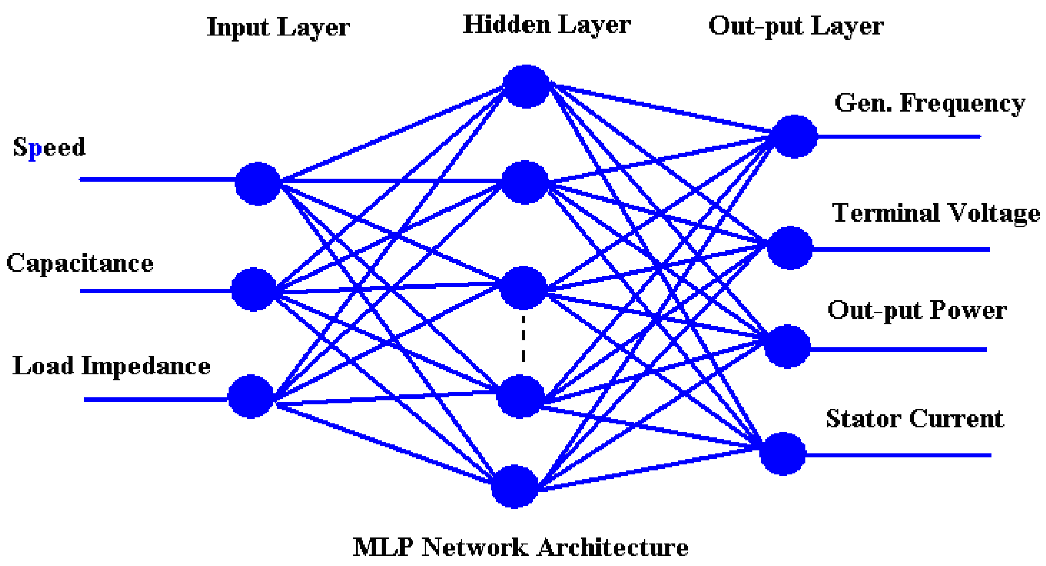

Figure 2: Feed forward artificial neural network.

Usually hit and trial method is applied to find the suitable ANN structure that depends on the input and output neurons. With lesser number of hidden layer neurons, network execution becomes faster but accuracy in terms of function approximation suffers. On the other hand, with more number of hidden layer neurons, though accuracy improves but network complexity increases. Thus, it necessitates identifying the optimum number of hidden layer neurons to establish sense of balance between function approximation accuracy and network complexity.

In this paper, an attempt is made to evolve a strategy for identifying the optimum number of hidden layer neurons based on Optimality Factor (OPF) obtained by varying the ratio of Error Weight (EW) and Network Complexity Weight (NCW). The optimal ANN structure is identified by comparing the acceptability of the network for different EW: NCW ratios, and is discussed in detail in section V. Further, the evolved optimal ANN architecture is used for performance analysis of SEIG with varying terminal conditions.

Algorithm for Identification of Optimal Ann

For identification of optimal ANN architecture, input-output data samples are taken from the analytical solution of SEIG operating at variables speed, capacitance and load. The input layer has three neurons accounting for three inputs namely: speed 'b', capacitance 'C' and load 'R_L. The output layer has four neurons that account for the four outputs namely: generated frequency 'a', output voltage 'V_t' and output power 'P_o'and stator current 'I_s'. Varying the hidden layer neurons from 4 to 16, the performance of different networks is compared. The step-wise procedure adopted to identify optimal ANN architecture is detailed as under:

- From the analytical solution of SEIG, one thousand input-output samples are generated with randomly chosen input variables for the training of different networks.
- For identification of optimal ANN structure, thirteen ANN architectures are chosen with 4-16 neurons in hidden layer.
- Twenty-five sets of weights and biases are randomly chosen initially to train each ANN structure. ANN architectures are first trained for 200 epochs using Levenberg Marquardt (LM) algorithm.
- The performance of each trained ANN structure is recorded using validation data (15% of the input-output training samples, other than training data).
- Out of the 25 sets of weights of each network structure, weights of ten sets were selected that give minimum sum-squared error with validation data. The rest of the sets of weights for each network are ignored.
- With 10 sets of selected weights, each ANN architecture is further trained for 300 epochs to reduce training SSE.
- The performance of each network is recorded in terms of average SSE and network complexity for validation samples.
- Optimality factor of each network structure is evaluated by varying the EW and NCW ratio from 20:80 to 80:20.
- On the basis of optimality factor and per unit acceptability of each network for different EW: NCW ratios, the optimal ANN structure is identified.

Identification Of Optimal Ann Architecture and Its Implementation

In this work, emphasis is given to identify optimal ANN architecture for a specific application for analysis of SEIG. The algorithm described in section IV is used to determine the optimal ANN network. The ANN networks having different neurons (4 to 16) in hidden layer are trained with 1000 randomly generated input-output training samples obtained from analytical solution of SEIG with varying speed, capacitance and load. The performance of trained ANNs is recorded using validation data samples (other than training samples). After giving training at each stage, the values of average value of SSE and network complexity are computed for each network. The SSE and network complexity both are normalized to obtain Normalized Sum-Square Error (NSSE) and Normalized Network Complexity (NNC). Optimality Factor (OPF) of each network is evaluated by varying the ratio of Error Weight (EW) and Network Complexity Weight (NCW) from 20:80 to 80:20. The results obtained for different networks with varying ratio (EW: NCW) are given in Table 1.

In practical situations, the requirements of a user may differ considerably. One user may give more significance to accuracy i.e. smaller value of SSE while another user may require small training times to employ on-line learning which may necessitate smaller network complexity. These two factors act opposite to each other and need to be judiciously balanced depending upon the requirement of the user. Thus, to determine the optimal number of hidden layer neurons in the network, the term Optimality Factor (OPF) is introduced which is expressed in terms of EW and NCW.

Table I: Optimality Factor of Different ANN Networks with Varying Ratio (EW: NCW).

RATIO (EW: NCW) →	20:80	30:70	40:60	50:50	60:40	70:30	80:20
Hidden Layer Neurons	Optimality Factor						
4	0.2600 *	0.3400	0.4200	0.5000	0.5800	0.6600	0.7400
5	0.2763	0.3312	0.3860	0.4408	0.4957	0.5505	0.6053
6	0.2975	0.3296 *	0.3617 *	0.3938 *	0.4259	0.4580	0.4901
7	0.3416	0.3625	0.3833	0.4041	0.4249	0.4457	0.4666
8	0.4010	0.4182	0.4354	0.4525	0.4697	0.4869	0.5040
9	0.4263	0.4228	0.4193	0.4158	0.4122	0.4087	0.4052
10	0.4745	0.4617	0.4490	0.4362	0.4235	0.4107	0.3979
11	0.5177	0.4932	0.4687	0.4443	0.4198	0.3953	0.3708
12	0.5491	0.5070	0.4649	0.4228	0.3807	0.3386	0.2965
13	0.5891	0.5336	0.4781	0.4226	0.3672 *	0.3117 *	0.2562
14	0.6427	0.5806	0.5186	0.4566	0.3946	0.3326	0.2706
15	0.6878	0.6151	0.5423	0.4696	0.3968	0.3240	0.2513*
16	0.7400	0.6600	0.5800	0.5000	0.4200	0.3400	0.2600

*minimum value of optimality factor of different ANN structures with fixed ratio (EW: NCW)

$$\text{Optimality Factor} = \text{NSSE*EW} + \text{NNC*NCW} \qquad (5)$$

From the results, it is observed that OPF is lowest for network with 15 neurons in hidden layer having almost zero importance given to complexity and nearly complete emphasis given to SSE. The next lowest OPF is observed in case of 4 hidden layer neural network for almost nil significance to SSE and complete significance attached to complexity. But, these are extreme situations and are seldom desirable in practical applications. On the other hand, considering per unit value of acceptability of other networks, the ANN with 6 hidden neurons proves to be most acceptable. Its performance based on OPF is optimal three times for a particular EW:NCW ratios of 30:70, 40:60 and 50:50. Thus, its per unit acceptability is highest i.e. 0.4286 per unit. ANN structure with 13 hidden layer neurons is acceptable twice with EW: NCW ratios of 60:40 and 70:30 and attains 0.2857 per unit acceptability. Per unit acceptability of networks with different hidden layer neurons is shown in Fig. 3.

In practical situations, the requirements of a user may differ considerably. One user may give more significance to accuracy i.e. smaller value of SSE while another user may require small training times to employ on-line learning which may necessitate smaller network complexity. These two factors act opposite to each other and need to be judiciously balanced depending upon the requirement of the user. Thus, to determine the optimal number of hidden layer neurons in the network, the term Optimality Factor (OPF) is introduced which is expressed in terms of EW and NCW.

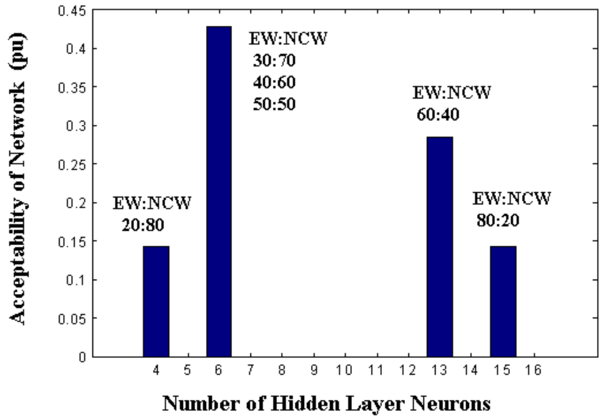

Figure 3: Per unit acceptability of network with different hidden layer neurons.

Networks with 4 and 15 neurons in hidden layer have the least acceptability of 0.1428 per unit, where as rest of the ANN structures have zero acceptability. From the results, it is noticeable that ANN network with 6 hidden layer neurons has wider acceptability and can be considered to optimal for performance analysis of SEIG under the given set of terminal conditions

The optimal ANN architecture (3-6-4) identified is further trained with Successive Over-relaxation Resilient Backpropagation (SOR-RPROP) algorithm [16] using same training data. The training SSE goal is fixed at 0.01. Learning rates for hidden and output layers is set at 0.01. The error goal is achieved in 9635 epochs. The trained ANN model is implemented for analysis of SEIG under varying speed, terminal capacitance and load situations. The results obtained from ANN model of SEIG are also verified with experimental data of machine with specifications given in Appendix-I. The closeness of the results confirms the validity of model. The graphical representation of results is shown in Fig. 4 to 7.

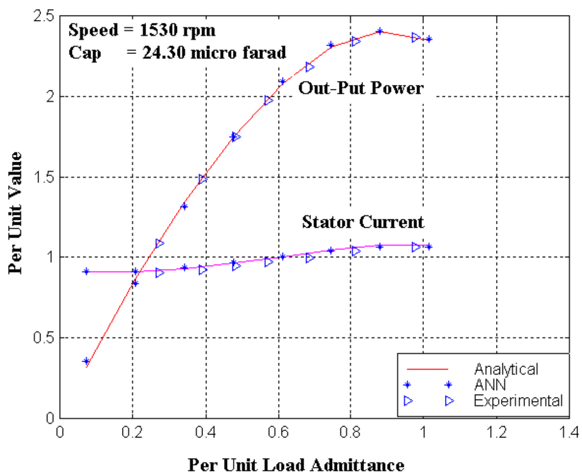

Figure 4: Out-put power and stator current v/s load admittance.

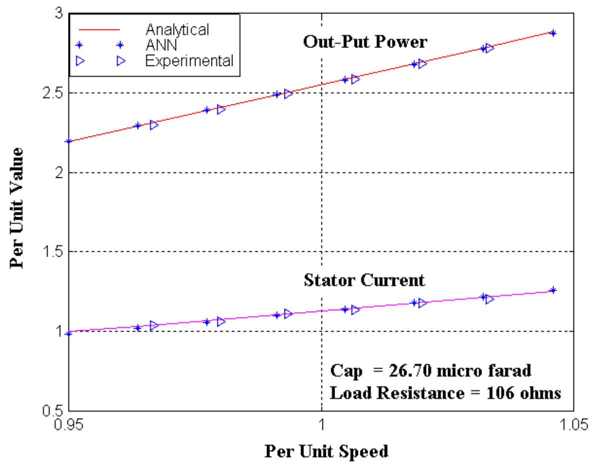

Figure 6: Out-put power and stator current v/s speed.

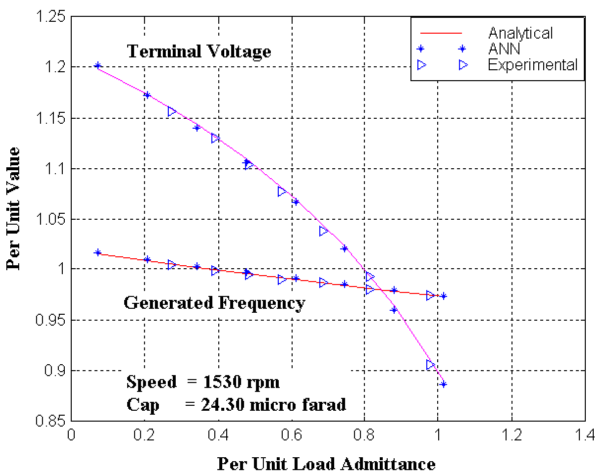

Figure 7: Terminal voltage and generated frequency v/s load admittance.

Conclusions

In this paper, a strategy for exploring optimal network structure for ANN based model of SEIG is presented. It is a well-known fact that with small number of hidden layer neurons, the network becomes quicker in training and execution times. But, small networks may not be able to approximate the function to desired level of accuracy. With more number of hidden layer neurons, function approximation accuracy improves but network complexity increases. Thus, to establish balance between function approximation accuracy and network complexity, it is essential to identify the optimum number of neurons in hidden layer. In this paper, an attempt has been made to explore a strategy for identifying the optimal number of hidden layer neurons based on optimality factor obtained by varying the ratio of EW and NCW. The network with minimum OPF for a particular ratio of EW:NCW and having overall highest per unit acceptability is considered to be optimal.

Optimal network does not mean that it provides the best solution. Optimal indicates that the network is the best amongst the networks explored in this work for the specific application. Therefore, there still exists considerable scope for improvement in identification of optimal ANN structure. The issue of number of hidden layers in the network has not been considered in this paper. Therefore, the strategy of identifying the optimal network structure can be further extended to include multiple hidden layers.

The evolved single hidden layer optimal ANN architecture is used for performance analysis of SEIG with sufficient accuracy. To validate the results of ANN based model of SEIG, the results are compared with those obtained from classical Newton-Raphson method and experimental data. The closeness of results confirms the validity of the ANN model and justifies the strategy adopted for identification of the optimal neural network.

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Appendix-I

Machine Specifications:

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

Machine parameters in ohms

$R_s = 5.76\,\Omega$	$R_r = 4.19\,\Omega$
$X_{ls} = 9.37\,\Omega$	$X_{lr} = 9.37\,\Omega$

About the author

Raja Singh Khela was born in India in 1956. He passed three year diploma course (with honours) in Electrical Engg. from PSBTE, Chandigarh in 1977, He graduated in Electrical Engg. from Institution of Engineers, Calcutta in 1985 and did Master’s degree (with Distinction) in Electrical Engg. from Punjab University, Chandigarh (India) in the year 1990. He did his PhD in 2009 from Punjab Technical University, Jallandhar (India). His major field of study is power systems and is working in the area of analysis of self-excited induction generator using AI techniques.

He served as Demonstrator / Lecturer with J. R. Govt. Polytechnic Hoshiarpur from 1978 to 1991. He has served as Associate Professor at GZS College of Engg. & Technology, Bathinda, Punjab from 1991 to 2009 and presently serving as Director-Principal with Sri Sai Group of Institutes Badhani-Pathankot, Punjab, India. He has published numerous research papers in national and international journals and conferences. His research papers include applications of artificial intelligent techniques in power systems.