Artificial Neural Network-Based Electronic Load Controller for Self-Excited Induction Generator

S. Karmakar and S.N Mahato
Department of Electrical Engineering
National Institute of Technology
Durgapur-713209, India
shukla.k1317@gmail.com, snmrec@yahoo.co.in

Abstract: **This paper deals with the performance analysis of a 3-phase Self-Excited Induction Generator (SEIG) incorporating an artificially intelligent Electronic Load Controller (ELC). ELCs are used to maintain a constant voltage at the generator output terminals. Intelligent ELCs employing the Bayesian Regularization and the Levenberg Marquardt algorithms of Artificial Neural Network are used as the control techniques. These are implemented in SIMULINK and adequate results are obtained.**

Keywords: Electronic load controller; Self- Excited Induction Generator; Bayesian Regularization; Levenberg Marquardt algorithm.

I. Introduction

In many remote areas, the supply of electricity through the grid becomes troublesome and costly. In such areas exploiting renewable energy resources to produce electrical energy is an acceptable alternative. Hydro-energy is the most dependable substitute among the other non-conventional energy resources. Areas, where water streams and rivulets are available; installing a pico-hydro power plant, is economical for stand-alone electrical power generation. In such cases, Self-Excited Induction Generators (SEIGs) are preferred for the generation of electricity [1]-[4].

The demerit associated with SEIGs is that it fails to regulate the generator terminal voltage with the variation in consumer loads. To overcome this problem, an Electronic Load Controller (ELC) is used in conjunction with the SEIG [5][6].

The ELC considered comprises a three-phase uncontrolled rectifier circuit, a chopper switch, and a ballast load. The performance of ELCs equipped with a Proportional Integral (PI) controller and an Artificial Neural Network (ANN) based controller is evaluated.

ANN is an efficient soft computing tool that imitates the human nervous system for solving complex problems. Also, it is effectively applied in controllers as found in the literature [7]-[9]. The Bayesian Regularization (BR) and the Levenberg Marquardt (LM) algorithms of ANN are implemented in this paper. These are used to control the switching order of the chopper.

II. System Illustration

The variation of consumer load or main load is balanced by the ELC. This is done by regulating the amount of power that is dumped in a resistive load, which is often known as the ballast load or dump load. Heaters are generally used as the ballast loads. Figure1 shows the diagrammatic representation of a three-phase SEIG-ELC system.

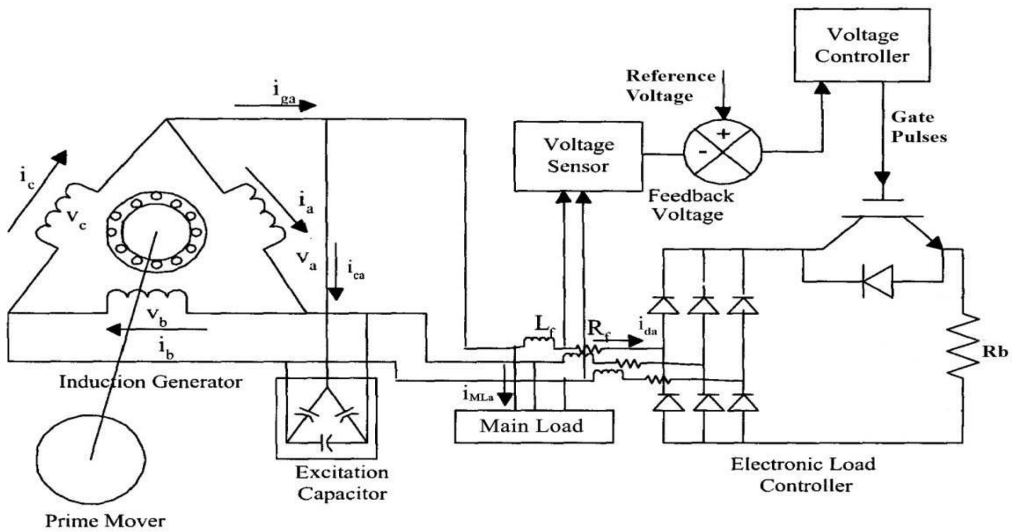

Figure1.Simplified diagram of a three-phase SEIG with ELC

The figure shown above represents a system comprising a 3-phase delta-connected SEIG connected to an excitation capacitor bank, the main load, and the ELC. The chopper switch used in the ELC circuit is an Insulated Gate Bipolar Transistor (IGBT). The chopper is driven by gate pulses obtained from the output of a voltage controller. The switching succession of the chopper is controlled in such a way that a constant voltage and hence a constant power is maintained at the generator output terminals.

III. MODEL OF ELECTRONIC LOAD CONTROLLER

The peak ac input voltage to the ELC can be calculated as

$$V_{ac(p)} = \sqrt{2}\times V_L = \sqrt{2}\times 230 = 325.27\ \text{V} \qquad (1)$$

Here V_L is the Root Mean Square (RMS) value of the generator phase voltage. During transient circumstances, an overvoltage of 10% of the rated voltage of the generator may appear at the input of the ELC. Thereby the peak ac input voltage for such condition will be

$$V_{ac(p)} = \sqrt{2}\times (V_L + 0.1 \times V_L) = 357.79\text{V} \qquad (2)$$

The dc output voltage of the three-phase uncontrolled rectifier may be calculated as

$$V_{dc} = (3\sqrt{2}\ V_L)/\prod = 310.61\text{V} \qquad (3)$$

The rectifier and chopper of the ELC have a voltage rating determined by the RMS value of ac input voltage to the rectifier and average value of dc output voltage from the rectifier. The current rating for the same can be calculated as

$$I_{ac} = P/ (\sqrt{3}\times V_L) = 5.52\text{A} \qquad (4)$$

where P indicates the power rating of the 3-phase SEIG. The peak ac input current to the ELC can be determined by accounting a distortion factor of 0.95 and a crest factor of 2.0 for the three-phase rectifier as follows

$$I_{ac(p)} = (I_{ac}\ /0.95)\times 2 = 11.63\text{A} \qquad (5)$$

The resistance of the ballast load (Rb) may be calculated as

$$Rb = (V_{dc})^2 / P = 44\Omega \qquad (6)$$

IV. ARTIFICIAL NEURAL NETWORK-BASED ELECTRONIC LOAD CONTROLLER

ANN consists of processing units (neurons) interconnected to form a network. A suitable learning algorithm can be used to train the network and therefore minimize the error between the target outputs and actual outputs of a system [10]. The BR and LM algorithms of ANN are used for the purpose. The output of the network is correlated with a saw tooth carrier waveform to produce gating signals. The gate pulses are then fed to the chopper to act. The representation of ANN is shown in Figure2.

a. Bayesian Regularization (BR) algorithm: Regularization improves network performance by modifying the performance function. The performance function is the sum of the square of error and the sum of the square of network weights [11]-[13]. Figure3 shows the function approximation and Figure5 shows the error minimization by the BR algorithm.

b. Levenberg Marquardt (LM) algorithm: The LM algorithm reduces the error by minimizing the performance function [14]-[16]. The performance function is the mean of the square of the approximate relationship between the inputs and outputs of a system. Figure4 shows the function approximation and Figure6 shows the error minimization by the LM algorithm.

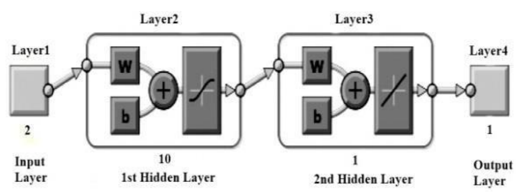

Figure2. Representation of ANN

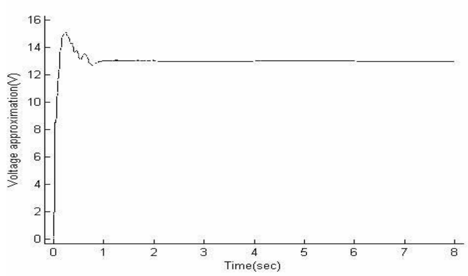

Figure3. Function approximation by BR Algorithm

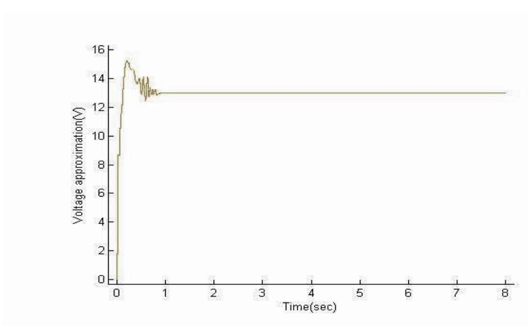

Figure4. Function approximation by LM Algorithm

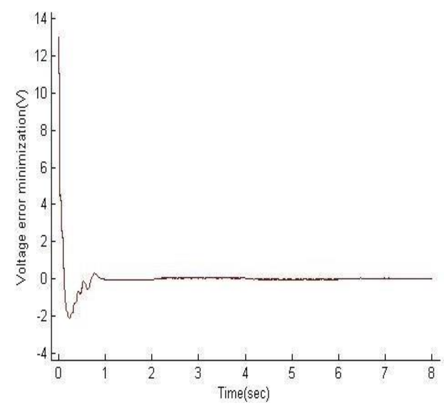

Figure5. Error minimization by BR Algorithm

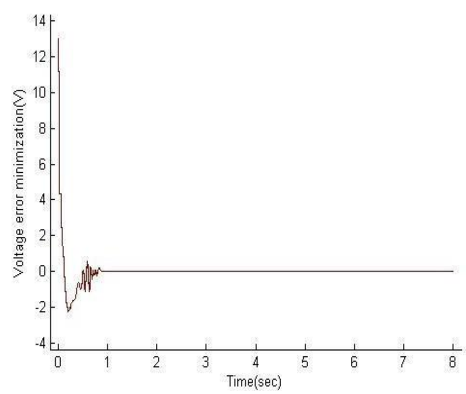

Figure6. Error minimization by LM Algorithm

From the graphs obtained, it is found that the LM algorithm has a better function approximation and error minimization capability over the BR algorithm.

V. Results And Discussion

SIMULINK in MATLAB has been used to model a three-phase, delta connected, 2.2KW, 230V, 7.78A Self-Excited Induction Generator. A capacitor bank of capacitance 50μF per phase is connected for excitation of the SEIG. The main load on the generator is varied from an initial value of 26.45W to 352.67W, 52.9W, and 293.89W at 2 seconds (sec), 4 seconds and 6 seconds respectively. Simulated results obtained without using ELC and using PI controller based ELC are shown in Figure7 and Figure8 respectively.

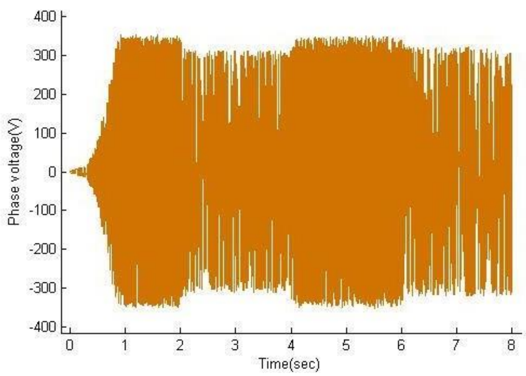

Figure7: SEIG phase voltage without using ELC.

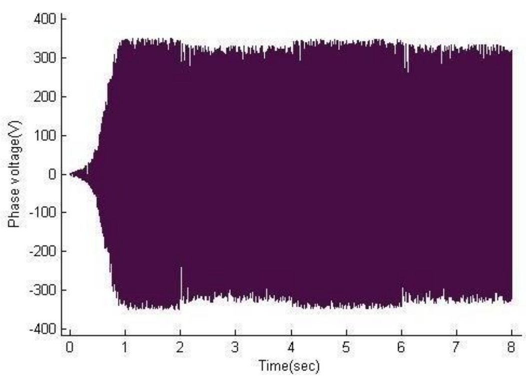

Figure8: SEIG phase voltage with using ELC.

From Figure7 and Figure8, it is seen that ELC using a PI controller is capable of regulating the SEIG output voltage.

Figure9 and Figure10 represent the controlling efficiency of the ELC utilizing the BR and the LM algorithms of ANN respectively.

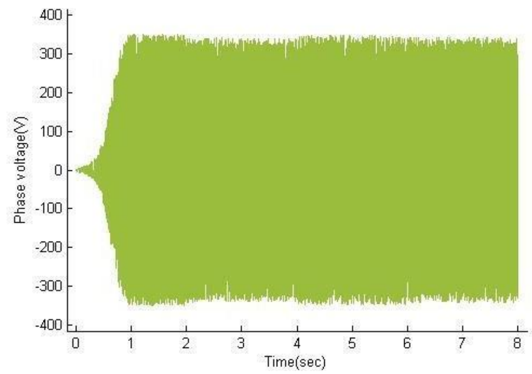

Figure9: SEIG phase voltage using the BR algorithm.

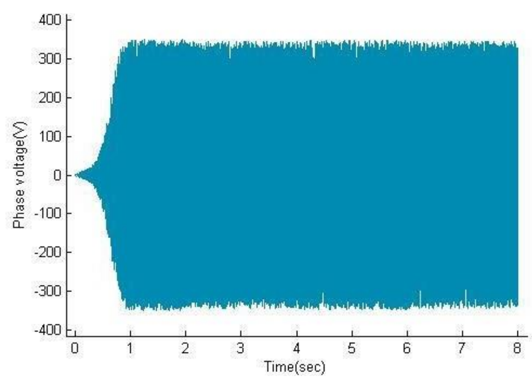

Figure10: SEIG phase voltage using the LM algorithm.

From Figure9 and Figure10, it is seen that ELC employing the LM algorithm has better controlling efficiency than the BR algorithm.

From the results obtained, it can be comprehended that both the ANN-based algorithms used as control techniques are more efficient than the conventional controller. Both algorithms are having good perfection, while the LM algorithm gives a more accurate and stable convergence.

VI. CONCLUSION

The performance evaluation of the three different control techniques employed in the SEIG-ELC system has been done. The results achieved infer that the ANN controllers are very much suitable to be used in ELCs. Thereby these technologies can be productively applied in SEIG-ELC systems for supplying a regulated voltage and hence a regulated power at varying consumer loads.

APPENDIX

The parameters of the considered machine are as follows:

3-phase, delta connected, 2.2KW, 230V, 7.78A, 4 pole, 50 Hz, X_{ls}=0.00442 kΩ, X_{lr} = 0.00442 kΩ, R_s = 0.00288k Ω, R_r = 0.00288 kΩ, C = 50µF.

The relation between the magnetizing inductance (L_m) and the magnetizing current (I_m)of the machine is expressed as:

$$L_m = \begin{cases} 0.3177 & \text{for } I_m \leq 0.75 \\ 0.3502 - 0.0349\, I_m - 0.0017 I_m^{\,2} & \text{for } 0.75 < I_m \leq 4.25 \\ 0.17667 & \text{for } I_m > 4.25 \end{cases}$$

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