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Application of Artificial Neural Networks to Control the Output Voltage of Wind Energy System

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Abstract :

This paper presents the use of Artificial Neural Networks to control the output voltage of Self-Excited Induction Generator (SEIG) driven by wind turbine and supplies static load. The effects of rotor speed, load impedance and the excitation capacitance variations on the terminal voltage of the SEIG are discussed. An adaptive controller scheme based on Artificial Neural Networks (ANNs) is proposed to predict the suitable value of regulator capacitance for maintaining a constant output voltage of the SEIG. A programmable high speed controller (PHSC) is used to switch ON the required capacitor for providing the predicted capacitance. A Matlab simulation results are presented to demonstrate the terminal voltage of the SEIG with the proposed control scheme. The results proved that the proposed scheme is able to keep the terminal voltage at constant value in spite of the wind speed and load variations.

Keywords: wind generation, output voltage control, artificial neural networks.

تطبيق الشبكات العصبية الصناعية الذكية للسيطرة على الجهد الخارج لنظام طاقة الرياح

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الخلاصة :

يتضمن هذا البحث استخدام الشبكات العصبية الصناعية الذكية للسيطرة على الجهد الخارج من مولد حثي ذو ألإثارة الذاتية المرتبط بتوربين رياح و المجهز لحمل استاتيكي. تم مناقشة تأثير تغير السرعة و ممانعة الحمل و متسعة الإثارة على جهد إطراف المولد ألحثي. تم اقتراح مسيطر متكيف يعتمد على الشبكات العصبية الصناعية الذكية للتنبؤ بقيمة متسعة الإثارة للحفاظ على جهد خارج ثابت للمولد ألحثي. تم استخدام متحكم مبرمج عالي السرعة لتشغيل و إدخال المتسعة المطلوبة و المتوافقة مع المتسعة المتنبؤ بها. تم استخدام برنامج ماتلاب لمحاكاة تغير جهد إطراف المولد مع النظام المقترح. أثبتت النتائج إن النظام المقترح قادر على الحفاظ على جهد إطراف ثابت للمولد ألحثي على الرغم من تغير السرعة و ممانعة الحمل.

List of Principal Symbols

a frequency of the generator e.m.f / base frequency.

b actual rotor speed / synchronous speed according to base frequency.

C total regulator capacitor

$C_{exc.}$ self - excitation capacitance per phase (farad)

E1 air gap voltage (volt).

L_1, L_2, L_m stator, rotor and magnetizing inductances (henery)

L_L load inductance (henery)

N rotor speed (rpm)

R_1 , R_2 , R_L stator, rotor and load resistances per phase (ohm)

V_t terminal voltage of SEIG

X_c capacitive reactance (ohm)

X_L load reactance (ohm)

X_m magnetizing reactance (ohm)

1. Introduction

The wind energy industry is at the forefront of the world's shift away from reliance on fossil fuels. In just a few short decades wind energy has evolved dramatically. Technological advances make wind energy a cost-effective solution for the world's ever-growing energy needs [1]. The worldwide wind capacity reached 254 GW out of which 16.546 GW was added in the first six months of 2012 [2]. Twelve newer EU Member States in Central and Eastern Europe plan to increase wind power capacity from the 6.4 GW installed at end of 2012 to 16 GW by 2020. This is equivalent to the electricity supply of 9 million households [3]. A few of the technological challenges such as adopting variability of wind power, power quality issues, are yet to be solved, however, the combined efforts from researchers and scientists will ensure its fastest growth [4]. The SEIGs have been found suitable for many applications such as wind, tidal, and small hydroelectric energy conversion in the past few years. SEIG has many advantages such as brushless construction, reduced size, absence of DC power supply for excitation as in synchronous generators, reduced maintenance cost, well over speed capability, self-short circuit protection capability and no synchronizing problem [5].

ANNs are collections of individually interconnected processing units. Information is passed between these units along interconnections. For the modelling, prediction of performance and control of renewable energy process ANNs appear to be most applicable. ANNs have been used in diverse applications and play an important role in modelling and prediction of the performance and control of wind energy processes [6-12].

The need for adaptive regulating capacitance value comes from the fact that the wind turbine operates over a wide range of operating conditions, which means that the terminal voltage of the induction generator is not constant. Changing the value of regulator capacitance with the change of operating conditions (wind speed and loading conditions) can regulate the induction generator terminal voltage.

In this paper, an adaptive controller scheme based on Radial Basic Function Neural Network (RBFNN) is proposed to predict the suitable value of regulator capacitance for maintaining a constant output voltage of the SEIG. A programmable high speed controller (PHSC) is used to switch ON the required capacitor for providing the predicted capacitance. By using a Matlab (R2012a) the simulation results are presented to demonstrate the terminal voltage of the SEIG with the proposed control scheme.

2. Steady State Analysis of a SEIG [5]

Figure (1) shows the per-phase equivalent circuit commonly used for the steady-state analysis of the three-phase SEIG. The circuit has been transformed to the base frequency by introducing the parameters a and b, which are defined as:

a = frequency of generated e.m.f. / base frequency;

b = actual rotor speed / synchronous speed corresponding to base frequency.

For a given set of machine parameters, the terminal voltage V_t is expressed in terms of air-gap voltage E_1 and given by :

$$V_t = \frac{A.E_1}{\sqrt{B^2 + D^2}} \tag{1}$$

Where:

$$A = \sqrt{(X_L\ X_c\ a)^2 + (X_c\ R_L)^2}$$

$$B = \left(R_1 R_L\ a + X_L X_c a + X_1 X_c a - X_1 X_L\ a^3\right)$$

$$D = \left(R_1 X_L\ a^2 - X_c\ R_1 - R_L X_c + R_L\ X_1 a^2\right)$$

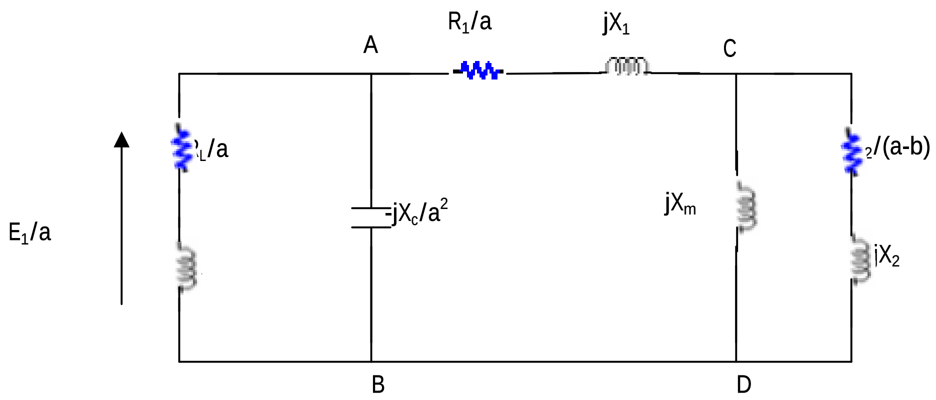


Fig. (1) Per-phase equivalent circuit of self-excited induction generator

The air-gap voltage E_1 is determined using the plot of (E_1/a) versus (Xm) shown in **Figure (2).**

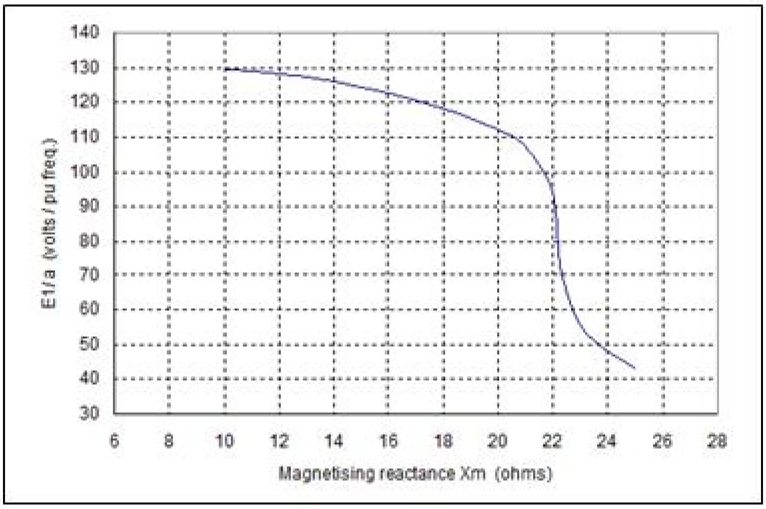


Fig. (2) Variation of normalized air gap voltage (E1/a) with magnetizing reactance (Xm)

3. Effect of Excitation Capacitance on Amplitude of Terminal Voltage

Equation (1) is used to demonstrate the effect of excitation capacitance on the terminal voltage of induction generator. The induction machine used as the SEIG in this investigation has the specification and parameters which given in appendix.

A Matlab (R2012a) is used to simulate the effect of rotor speed and load impedance on amplitude of SEIG terminal voltage (V_t). **Figure (3)** shows the variation of terminal voltage around a desired value (120 volts) against rotor speed at different values of excitation capacitance with constant load resistance of 70 ohms. **Figure (4)** shows the variations of terminal voltage versus the excitation capacitance at different values of rotor speed.

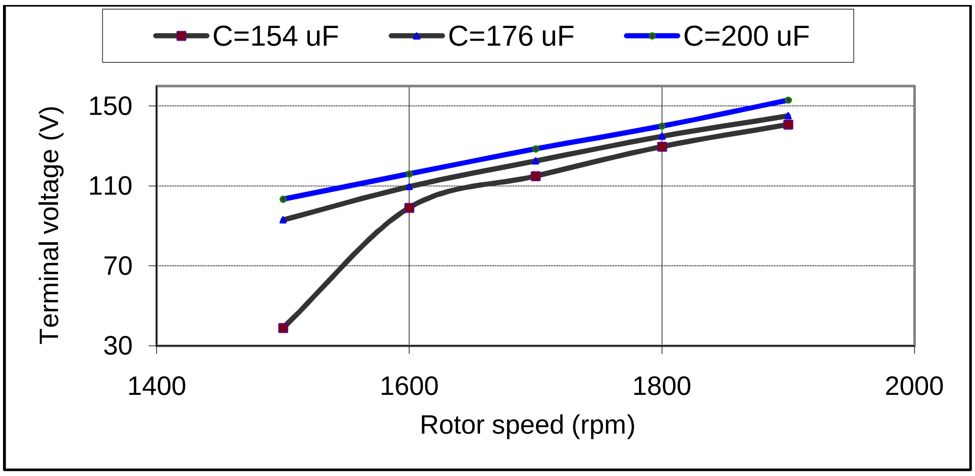


Fig. (3) Terminal voltage variation against rotor speed at different excitation capacitances

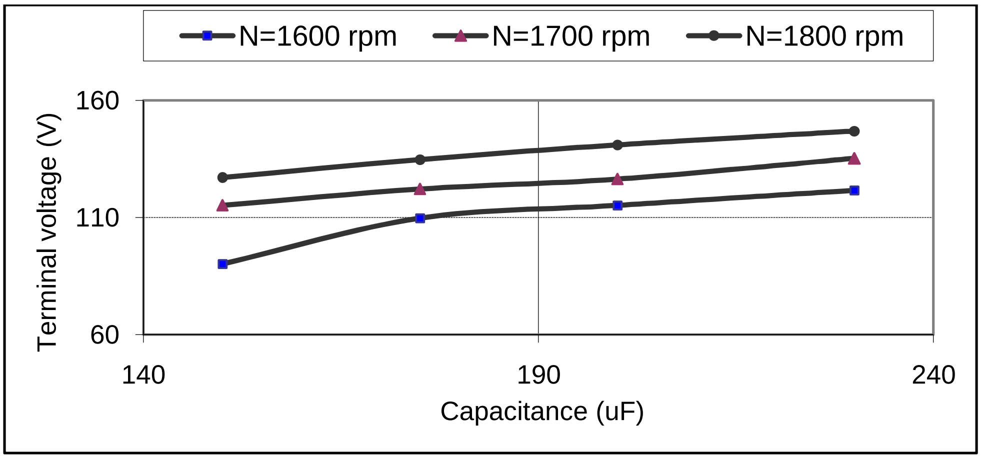


Fig. (4) Terminal voltage variation versus excitation capacitance at different rotor speeds

It can be noted that with constant value of excitation capacitance, if the rotor speed is decreased, the terminal voltage decreases also until critical speed is reached. If the rotor speed is decreased further, the generator fails to build up its own voltage. At fixed rotor speed, the terminal voltage rises if larger values of excitation capacitance are used.

Figure (5) shows the variation of terminal voltage (V_t) against the load impedance for different values of excitation capacitance and the speed is kept constant at 1700 rpm. With fixed load impedance, the terminal voltage increases if larger excitation capacitor is used instead of a smaller one. With constant value of excitation capacitance, the terminal voltage rises if the load impedance is increased.

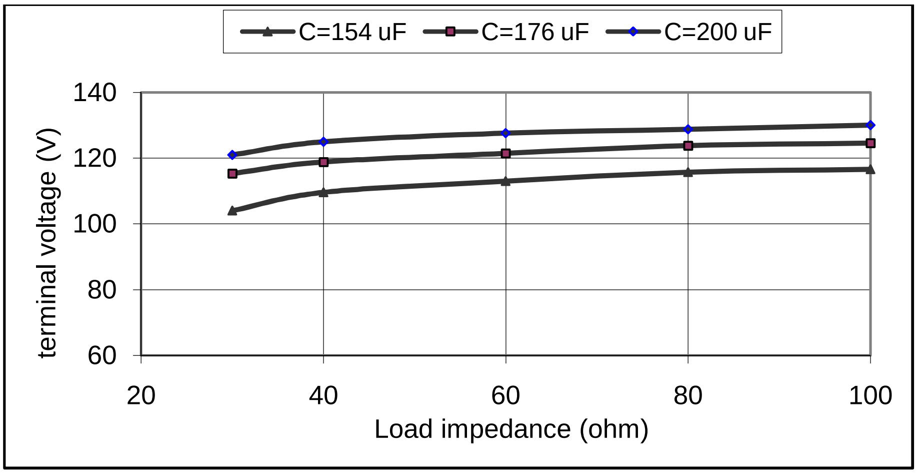


Fig. (5): Terminal voltage variation against load impedance at different values of excitation capacitance.

4. Radial Basis Function Neural Networks [6]

Radial basis functions neural networks (RBFNNs) have been developed based on the theory of radial basis for real multivariable function approximation. The use of RBFNNs in engineering applications is increasing rapidly. A RBFNN is three layers feed-forward neural network composed of input layer, hidden layer and output layer. The output units form a linear combination on the basis (kernel) functions computed by the hidden units as shown in **Figure (6).** The basis functions in the hidden layer produce a localized response to the input. That is, each hidden unit has a localized receptive field. The basis function can be viewed as the activation function in the hidden layer.

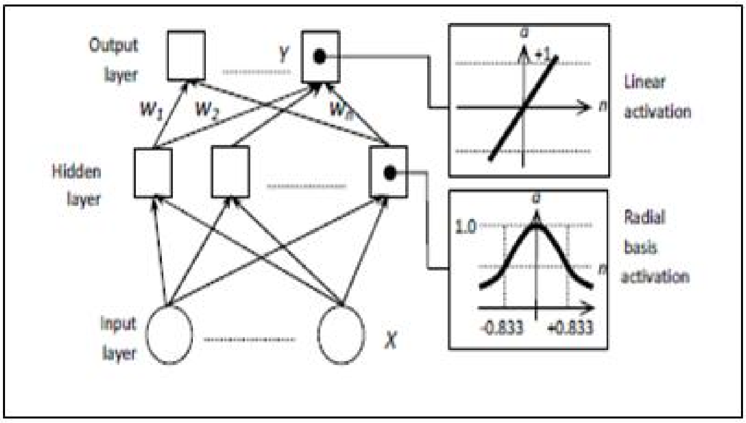


Fig. (6) Schematic diagram of radial basis functions neural network

Each output unit (Y) in the RBFNN performs the following function:

$$y_i(x) = \sum_{j=1}^{m} w_{ij}\, f_j(x) \quad ; \; i = 1, 2, ..., k \qquad (2)$$

where $f_j(x)'s$ are radially symmetric functions representing the nonlinearities in the hidden layer, W_{ij} is the weight from hidden unit j to output unit i, m is the number of neurons of hidden layer, and k is total output units of output layer. The most commonly used function is the Gaussian which given by:

$$f_j(x) = \exp\left(\frac{-(x - \hat{x}_j)^2}{2\, s_j^2} \right) \qquad (3)$$

The Gaussian function is defined by a center position $\hat{x}_j$ and a width (or spread) s_j. The center of the basis function can be determined by simple heuristic approaches, such as the k-means clustering method, and the width can be determined using nearest neighbor method. The number of hidden units can be selected as the number of training patterns. Different approaches have been proposed for the selection of the number of hidden units.

Learning in the RBFNN can be divided into two stages: learning in the hidden layer, followed by learning in the output layer. Typically, learning in the hidden layer is performed using unsupervised methods (i.e., does not depend on teaching patterns) such as the *k*-means clustering algorithm (clustering is concerned with grouping objects according to their similarity), while learning in the output layer uses supervised methods like the least mean square (LMS) algorithm. After the initial solution is found by this approach, a supervised learning algorithm (e.g., back-propagation) can be applied to both layers to fine-tune the parameters of the network, since the clustering algorithm does not guarantee an optimal set of parameters for the basis functions.

5. Adaptive Excitation Capacitor Based on RBFNN

A RBFNN can be conveniently created and tested by using neural network function in MATLAB toolbox. In this paper MATLAB (R2012a) is used to write script files for developing RBFNN. The command 'newrb' both defines the network type of training algorithm to be used and automatically initializes the network. The function newrb iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons have been reached. The call for this function is [7]:

net = newrb(P,T,GOAL,SPREAD)

where P represents the sequences matrix of input vectors, T is the output (target) vector, GOAl is the mean squared error goal and SPREAD is the spread of radial basis functions. The function newrb takes matrices of input and target vectors P and T, and design parameters GOAL and SPREAD, and returns the desired network. A command 'sim' is used to compare the output of the network with training data.

The proposed RBFNN consists of three layers; the input, hidden and output layers as shown in **Figure (7).** The input layer has two inputs; load impedance (ZL) and rotor speed (Nm), therefore, input layer neuron number is two. The activation radial basis function used in the hidden layer is Gaussian function with total number of (m) neurons. According to the algorithm of RBFNN, we can get the number of hidden neurons during the RBFNN training process automatically. Therefore, RBFNN has adaptive characteristics. The output layer has one output, which represents the prediction values of excitation capacitance ($C_{pred.}$); therefore, output layer neuron number is one.

At this time, for determining the value of spread, we change SPREAD value from 0.3 to 1.5 steps 0.1, and then we test these data during the neural network training, through comparing to get a better spread value, finally SPREAD get 1 with GOAL set to 0.1.

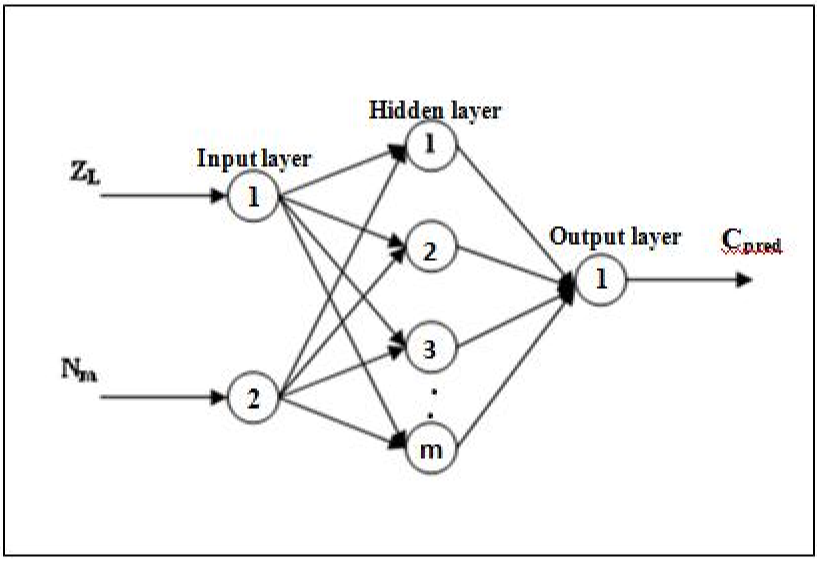
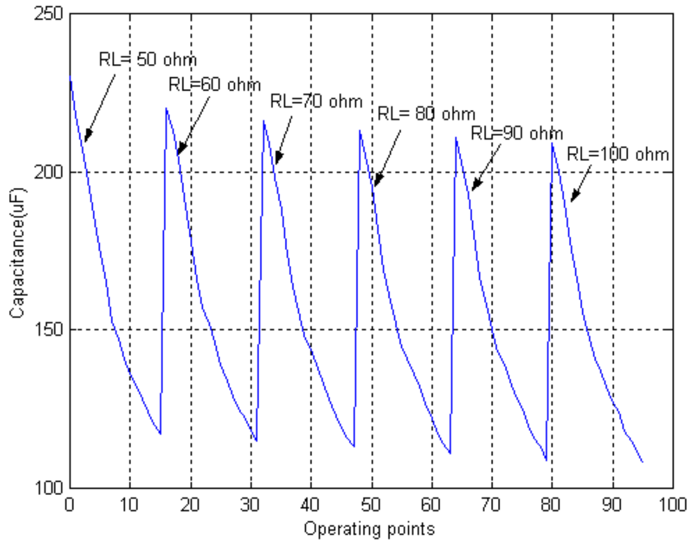


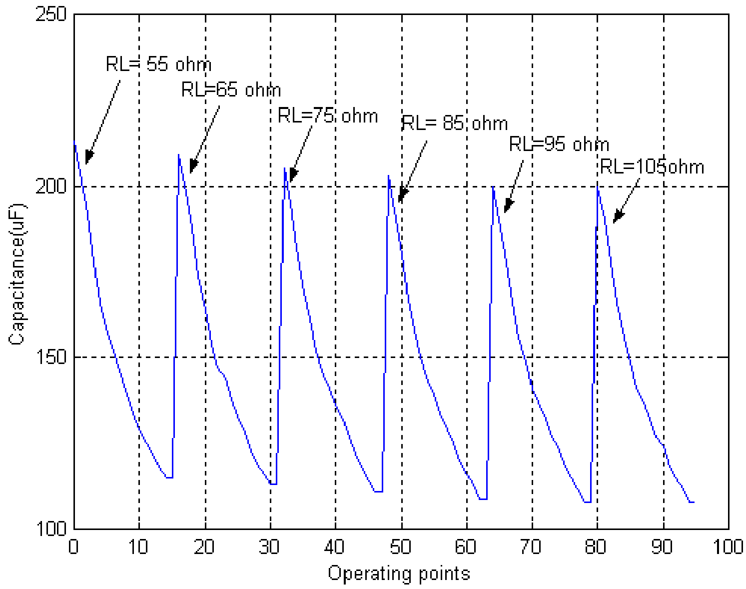
Fig. (7) Proposed radial basic function neural network.

The rotor speed is changed in steps of 20 from 1600 rpm, to 1900 rpm. The load impedance is increased gradually from 50 Ω to 100 Ω in steps of 10. Therefore, to train the network, 96 operating conditions are calculated by changing the rotor speed and load impedance. The excitation capacitance value for each operating point is calculated to keep the terminal voltage constant at rated voltage (120 V). The calculated values of excitation capacitance are used as an output target of the proposed neural network. The results of the training are shown in **Figure (8a).**

To test the generalization capabilities of the neural network, 96 operating conditions are used and the results of the test are depicted in **Figure (8b),** which shows that the RBFNN is able to predict the capacitor value for any operating conditions. The total neurons in the hidden layer (m) is found to be 46 and the mean square error (MSE) is 6.9638e-021.



(a)



(b)

Figure (8) Predicted excitation capacitance at different operation condition (a) Training results (b) Testing results.

6. Implementation of the Proposed System

Figure (9) shows the proposed wind turbine - SEIG voltage control scheme. A fixed excitation capacitor ($C_{exc.}$) and regulator excitation capacitor (C_1, C_2 , …. , Cn) banks are connected in parallel at the stator terminal of the induction generator. Regulator capacitors is used to stabilize the SEIG terminal voltage for a wide range of operating conditions while the fixed capacitor is responsible for voltage build up. In this scheme, the induction generator, regulator capacitor and neural network are interfaced to the programmable high speed controller (PHSC).

In **Figure (9),** a voltage and current sensors are used to measure the load impedance. The load impedance is equal the load voltage divided by the load current. A speed sensor is used to measure the generator's rotor speed. In practical a digital Avometer can be used to measure the rms values of load voltage and current. The rotor speed can be measured by a tachometer and an 8051 controller can be used as PHSC.

The RBFNN algorithm is used to adapt the desired regulator capacitor values for different operating conditions (different load impedances and rotor speeds).

The desired values of the regulator capacitance, which meet most of the expected operating conditions, are stored in a programmable high speed controller. A ladder program is used in the controller to compare the predicted value of the regulator capacitance with the desired one to decide which capacitor must be ON.

The firing angle of the thyristor is zero or π, i.e., the thyristor acts as a switch to turn ON the required capacitor. The firing signal of the thyristor which represented by a voltage signals is controlled by the PHSC.

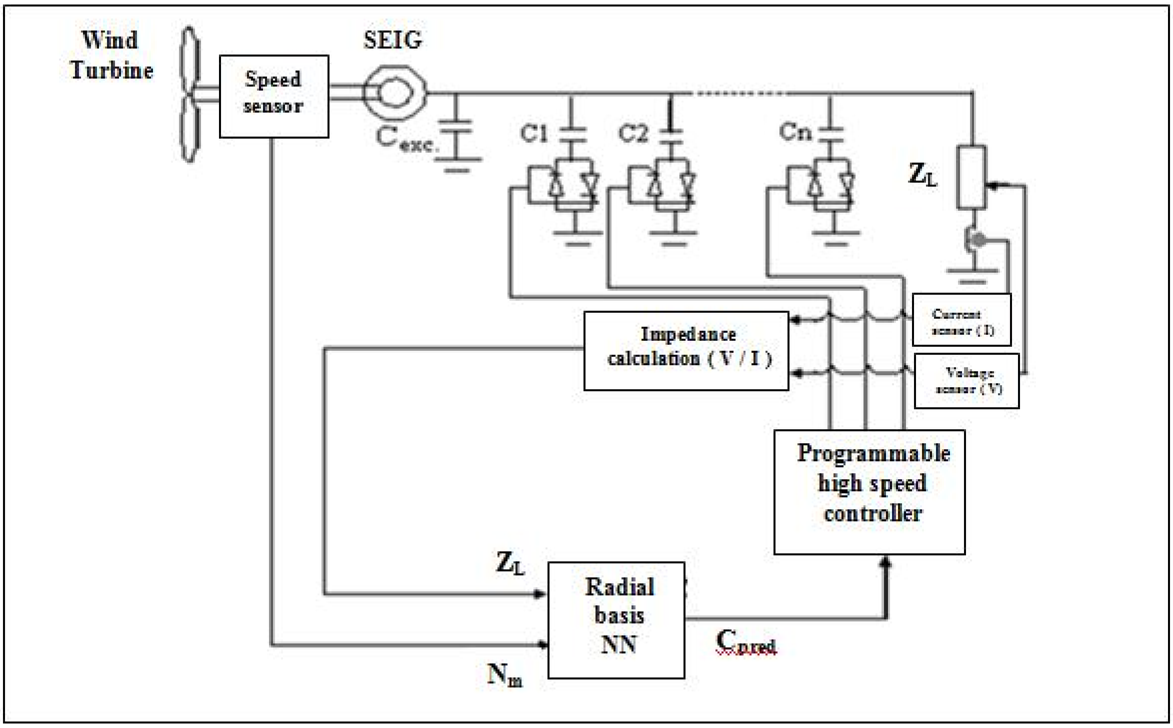


Fig. (9) Schematic diagram of the proposed system

7. Results and Discussions

To demonstrate the effectiveness of the proposed system for maintaining the terminal voltage of SEIG constant, comparison results between adaptive and constant excitation capacitors are investigated and explained in this section.

Firstly, assuming that the excitation capacitance value of the SEIG is kept constant at 174 μF and the rotor speed and the terminal load impedance are changed simultaneously for a specific period. As expected, the terminal voltage is not constant in this case, because it depends mainly on the rotor speed and the load impedance. Therefore, to keep the terminal voltage constant, an adaptation scheme based on the neural network and programmable high speed controller is used to adapt the excitation capacitance value.

Figure (10) shows the changed rotor speed with time in which each operating point represents a 50 second. The rotor speed is changed in step from 1700 rpm to 1750 rpm at operating point 1 (i. e. at 50 second), and then it is changed from 1750 rpm to 1660 rpm at operating point 2. Also, load impedance is changed simultaneously from 50 Ω to 80 Ω and then changed to 60 Ω as shown in **Figure (11).**

Figure (12) shows the variation of the excitation capacitance value with the simultaneous variation of the rotor speed and load impedance in comparison with the constant one (174 μF).

Figure (13) shows the corresponding variation of the terminal voltage of the SEIG with and without adaptive capacitance value. It can be noted that without adaptive capacitance the terminal voltage is increased to 130 V, but with adaptive capacitance the terminal voltage is constant at 120 V.

It is found that the value of the adapted capacitance swings between 148 μF and 185 μF to maintain the terminal voltage constant at rated value 120 V, with the corresponding variation of the rotor speed from 1660 rpm to 1750 rpm and the load impedance from 50 Ω to 80 Ω.

Generally, the proposed RBFNN is able to control successfully the terminal voltage of the SEIG by adapting the excitation capacitance for a wide range of operating conditions.

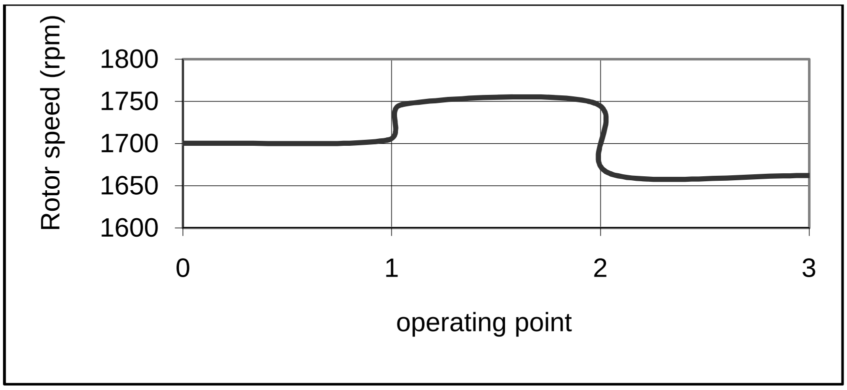


Fig. (10) Variation of the rotor speed

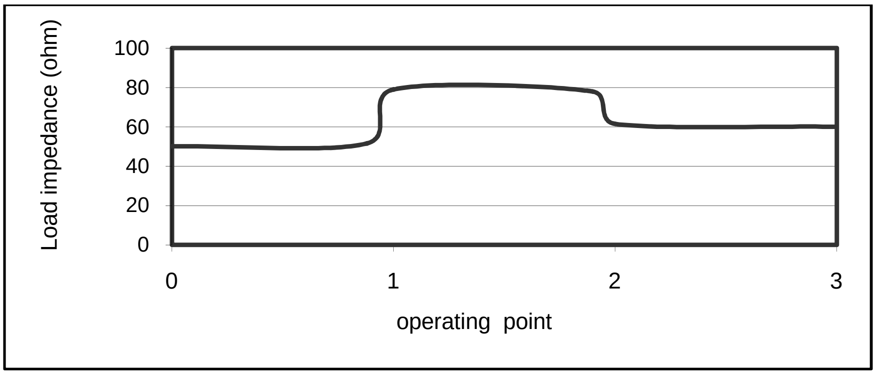


Fig. (11) Variation of the load impedance

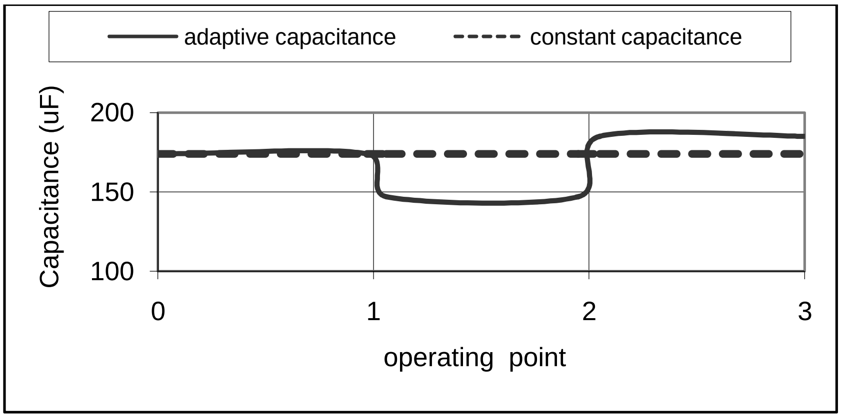


Fig. (12) Variation of the excitation capacitance

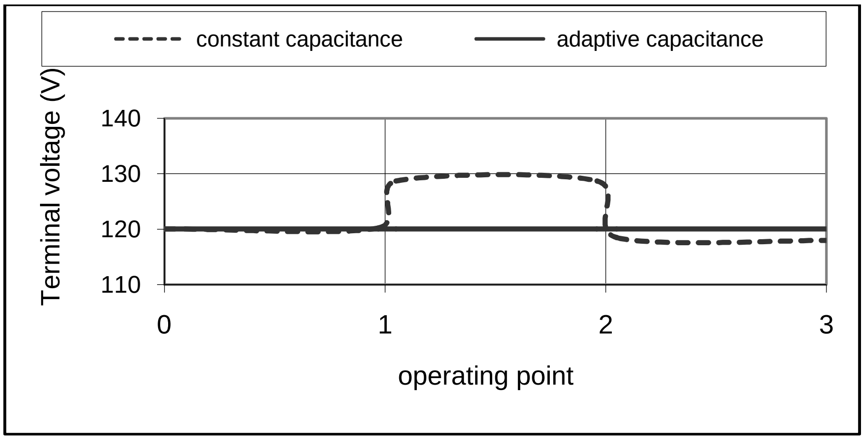


Fig. (13) Variation of the terminal voltage

8. Conclusions

In this paper, the output voltage of SEIG driven by wind turbine and supplies static load is controlled. A neural adaptive controller is used to control the generator terminal voltage at any operating condition. The use of an adaptive regulator capacitance value is motivated by the fact that the wind turbine generator operates over a wide range of operating conditions, and hence no single capacitance value is sufficient for regulating the terminal voltage. The RBFNN is used to predict the suitable value of regulator capacitor for any operating condition. Simulation results are presented to investigate the variation of terminal voltage when the rotor speed and load impedance are changed simultaneously with and without adapting the value of regulator capacitance. To maintain the terminal voltage of the SEIG constant at a desired value, large values of regulator capacitance are needed at low speed and small values of regulator capacitance are needed at high load impedance values and vice versa.

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Appendix

Specification and parameters of SEIG
Induction machine:
Rating: 3-phase, 2 kw, 120 V, 10 A, 4-pole, 1740 rpm.
Parameters: R1= 0.62 Ω, R2 = 0.566 Ω, L1 = L2 = 0.058174 H, Lm = 0.054 H.
Self-Excitation Capacitor:
Rating: 176 µf / phase, 350 V, 8 A.