Control of Self Excited Induction Generator using ANN based SVC

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ABSTRACT

This paper presents a terminal voltage control of a wind turbine Self Excited Induction Generator (SEIG). The wind turbine induction generator system is proposed to supply an isolated static load under widely varying conditions. The terminal voltage had been regulated by adapting the value of the excitation capacitance from Static VAR Compensator (SVC) using Artificial Neural Network (ANN) controller. 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 excitation capacitance by controlling the firing angle of SVC under different operating conditions can handle this problem. It is proved that SVC in the form of Fixed Capacitor -Thyristor Controlled Reactor (FC-TCR) is used not only provide capacitive excitation for the isolated induction generator, but also it controls its terminal voltage at all different loads with variable speeds of the windmill prime-mover. ANN is used for on-line prediction of the suitable firing angles required to control the terminal voltage of the system under different operating conditions.

Keywords

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Self Excited Induction Generator, Static VAR Compensator and Artificial Neural Network.

Nomenclature

| R_S, R_R, R_L | p.u stator, rotor and load resistances, |
|----------------------|---|
| | respectively |
| X_S, X_R, X_M, X_L | p.u stator, rotor leakage, magnetizing |
| | ,exciting and load reactances, at base |
| | frequency, respectively |
| Z _L | p.u load impedance |
| f_S | synchronous frequency |
| F | p.u frequency |
| v | p.u rotational speed |
| Eg, V_T | p.u air gap and terminal voltages. |
| | respectively |
| I_S, I_L | pu stator and load currents per phase, |
| | respectively |
| X_V | controllable reactance of SVC |
| λ | learning rate |
| μ | momentum factor |
| Ν | number of training iterations. |

1. INTRODUCTION

In recent years, it has been focused in new resources for electricity generation as wind, hydro...etc. The SEIG was used as the electromechanical energy converter in such generation schemes. The advantages of induction generators are low cost, robustness, absence of moving contacts and no need for DC excitation. The cost of an induction generator is about 40% - 50% of that of a synchronous generator of the same capacity. The SEIG is capable of generating electrical energy from constant speed as well as variable speed prime movers. Such an energy system can feed electrical energy to isolated locations, which in turn can enhance agriculture production and improve the standard of living in remote areas.

The magnitude of the terminal voltage of a SEIG depends upon the load impedance, excitation capacitance, and speed of the prime mover. The acceptability of such units depends upon the capability of the control system, which will provide constant voltage at different loads and different speed. Many investigations on the suitability, steady state analysis and output control of three phase SEIG have been made [1-5].

SVC are widely used in power systems for several applications [6]. They are mainly used in voltage control purposes and in stability problem solutions. They are used for solving machine operation problems such as induction motor starting and induction motor short circuit problems solutions [7-11].

Recently, there have been excessive and attractive schemes of neural network used in power system control since they hold a promising future to solve problems that have so far been difficult to handle with classical analytical methods. Among these control schemes, the back propagation based neural network controllers, which are mostly used in identification and adaptation control problems [12]. In back propagation control scheme, learning is divided into general and specialized learning. In general learning makes the input space of the plant with training samples so that the network can interpolate for intermediate points [13]. The specialized learning learns directly evaluating the accuracy of the network which is given by the error between the actual and desired outputs of the plant. The error evaluation updates the corrective weights in the network. In this sense, the controller learns continuously and hence it can control plants with timevarying characteristics.

In this paper, a variable speed windmill driven induction generator is excited by ANN based SVC in order to control the terminal voltage under different loading conditions.

2. SYSTEM MODELLING

2.1 Steady State Analysis of Self-Excited Induction Generators

Fig. 1 shows the per-phase equivalent circuit commonly used for SEIG supplying an isolated static load. A three-phase induction machine can be operated as a SEIG if its rotor is externally driven at a suitable speed and a three-phase capacitor bank of a

sufficient value is connected across its stator terminals. When the induction machine is driven at the required speed, the residual magnetic flux in the rotor will induce a small e.m.f. in the stator winding. The appropriate capacitor bank causes this induced voltage to continue to increase until an equilibrium state is attained due to magnetic saturation of the machine.

When a SEIG is loaded, both the magnitude and frequency of the induced e.m.f are affected by: the prime mover speed, the capacitance of the capacitor bank and the load impedance.

The steady-state per-phase equivalent circuit of a SEIG, supplying a balanced resistive load, is shown in Fig. 1. From Fig. 1, the total current at node a may be given by:

$$E_1(Y_1 + Y_M + Y_R) = 0 (1)$$

Therefore, under steady-state self-excitation, the total admittance must be zero, since $E_1 \neq 0$ so

$$(Y_1 + Y_M + Y_R) = 0 \tag{2}$$

$$\operatorname{Re} al(Y_1 + Y_M + Y_R) = 0 \tag{3}$$

 $\operatorname{Im}_{Where} ag(Y_1 + Y_M + Y_R) = 0 \tag{4}$

$$Y_{1} = \frac{(Y_{L} + Y_{C})Y_{S}}{Y_{L} + Y_{C} + Y_{S}} \qquad Y_{C} = \frac{1}{-j(X_{C} / F^{2})}$$
$$Y_{S} = \frac{1}{(R_{S} / F) + jX_{S}} \qquad Y_{M} = \frac{1}{jX_{M}}$$
$$Y_{L} = \frac{1}{(R_{L} / F + jX_{L})} \qquad Y_{R} = \frac{1}{\frac{R_{R}}{F - V} + jX_{R}}$$



Fig. 1 Per-phase equivalent circuit of a SEIG.

Equations 3 and 4 are nonlinear equations for the four unknowns F, X_M , X_V and v. Two of these unknowns should be specified. The other two unknowns can be found by solving the two non linear equations. Different values of rotational speed v and the controlled value of the capacitance Xv are determined to control the output voltage then the frequency and X_M are calculated.

Based on the analysis introduced in [14, 15], a fifth order polynomial independent of X_M is extracted to calculate the frequency, then the values of X_M are calculated at different loading conditions.

2.2 SVC Modeling

FC-TCR is modeled in the form of a variable reactance X_{LSVC} , which consists of two shunt elements as shown in Fig. 2.

The first element is a fixed capacitor of capacitive impedance denoted by X_{CSVC} . The second element is part TCR whose reactive impedance is X_{LFSVC} with a bi-directional thyristor valves. Full conduction is obtained with a firing angle of 90°, with a maximum possible firing angle of 180°.As firing angles ranges from 90°, to 180°, the modes of operation of FC-TCR varies from inductive to capacitive modes as the firing angles increase.[6].



Fig.2 Schematic diagram of FC-TCR

The controllable reactance of the TCR part is X_{LSVC} , [16], which is defined by :

$$X_{LSVC} = X_{LFVC} \frac{\pi}{2\pi - 2\alpha + \sin(2\alpha)}$$
(5)

The effective reactance XV the FC-TCR is given by:

$$X_{V} = \frac{X_{LSXV} X_{CSVC}}{X_{LSXV} + X_{CSVC}}$$
(6)

2.3 Neural network controller for FC-TCR

Artificial Neural Networks are considered as a relatively new information processing technique. They can be defined as "a computing system made up of a number of simple, highly interconnected processing elements, which process information by its dynamic state response". A neural network consists of a number of very simple and highly interconnected processors called neurons, which are the analogy of the neurons in the brain [17]. The neurons are connected by a large number of weighted links, over which signals can pass. In the present application, three layers neural network (having an input layer, a hidden layer and an output layer) have been used, together with a tansigmoidal activation function and supervised training via a back-propagation technique, as shown in Fig. 3. The well known enhancement of introducing a momentum term in the weight updating formula has also been successfully applied to reduce training times and to help in avoiding premature convergence.

The weights of neural network are adapted effected by error signal comes from the difference between desired and actual firing angles. To optimize the network, its error function is formulated in such a way that is quadratic in terms of the parameters to be estimated.

The error function E is calculated as

$$E = \frac{1}{2} \sum \left(\alpha_r(m) - \alpha_L(m) \right)^2 = \frac{1}{2} \sum \overline{e(m)}^2$$
(7)

Where α_r is the actual firing angle and α_L is the desired target at any time k, during each time interval from m-1 to m, the backpropagation algorithm is used to update the connective weights w according to the relation

$$w_{ij}(n+1) = w_{ij}(n) - \lambda \frac{\partial E}{\partial w_{ij}(n)} + \mu \Delta w_{ij}(n-1)$$
(8)

A three-layer (input, hidden, and output) network is used for the neural controller.



Fig. 3 Schematic diagram of the construction of the adopted neural network model

3. SIMULATION RESULTS

As the excitation capacitance increases, the support of the terminal voltage is occurred, so terminal voltage increases to higher levels with the load variation as depicted in Fig.4.

The terminal voltage is also changed by the variation of the speed at different excitation capacitances as shown in Fig.5.



Fig.4 Variation of terminal voltage with load variation at different speeds.



Fig.5 Variation of terminal voltage with speed variation at different excitation capacitances.

Fig.6, indicates the variation of terminal voltage with excitation capacitances at different speeds. As the speed increases the terminal voltage is increased till reach the saturation at higher values of excitation capacitance, then the terminal voltage is nearly constant.



Fig.6 Variation of terminal voltage with excitation capacitances at different speeds.

The capacitance required Xv at each loading conditions in order to maintain the output voltage at 1.1 p.u is obtained, then the corresponding values of the firing angles required for control the excitation capacitance at each loading condition.

To train the neural network, 42 operating conditions are calculated by changing the per unit rotor speed and per unit load impedance. The excitation capacitance value for each operating point is calculated to keep the terminal voltage constant at 1.1 p.u. The rotor speed is changed in steps of 0.1 from 0.6 p.u., to 1.2 p.u. The load impedance is increased gradually from 0.8 to 5 p.u. The calculated values of excitation capacitance and the corresponding firing angles are used as an output target of the proposed neural network. The results of the training are depicted in Fig.7.

To test the generalization capabilities of the neural network, 40 operating conditions (rather than the training points) are used. The results of the test are depicted in Fig. 8, that shows that the proposed scheme able to predict the value of the firing angle for new operating conditions.

4. CONCLUSIONS

This paper introduces a novel technique, back-propagation based ANN controller, to control FC-TCR to control the output voltage of wind turbine SEIG. The new controller allows FC-TCR to excite the SEIG to maintain the output voltage at 1.1 p.u, at different loading conditions. The ANN used apply on line excitation of SEIG with the voltage control.

The use of an adaptive excitation 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. Simulation results are presented to investigate the variation of terminal voltage when the rotor speed and load are changed simultaneously, then the controller adjusts the terminal voltage at 1 p.u.



Fig.7, The predicted firing angles at different operating points used for training.



Fig.8, The predicted firing angles at different operating points obtained from the ANN .

Appendix A

The SEIG chosen for this study is a 3-phase, 4-pole, 50 Hz, 2 kW, 380V, 5.4 A,Y-connected squirrel cage induction machine whose per phase equivalent circuit parameters in pu are:

Rs=0.0982, Xs=0.112, Rr= 0.0621 and Xr = 0.952 base on [1].

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6. **BIBLIOGRAPHY**

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