Reactive Power Compensation using Neural Network-Based Fixed Capacitor-Thyristor Controlled Reactor

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Abstract- This paper discusses the use of Fixed Capacitor-Thyristor Controlled Reactor (FCTCR) controlled by neural network for reactive power compensation. Back-propagation algorithm was used to train the neural networks. The TCR provides continuously controllable reactive power only in the lagging power-factor range. In order to extend the dynamic controllable range to the leading power-factor domain, a fixed-capacitor bank is connected in shunt with the TCR. The reactive power can be compensated simultaneously by selecting an appropriate amount of capacitive/inductive compensation. The control circuit is governed by computer based neural network, which replaces the traditional discrete load switching and makes the capability of rapid and dynamic balancing of the system possible. The simulation results show that the neural network based FCTCR can give rapid responses to the reactive power required by the system.

Keywords- Fixed Capacitor-Thyristor Controlled Reactor (FC-TCR), reactive power compensation, Neural Network, back-propagation algorithm.

I. INTRODUCTION

THE increasing of various kind of electrical machines and all other types of inductive loads used in industry will cause the increasing of reactive power consumption in the electrical systems. Therefore, it is necessary to generate such amounts of reactive power to compensate the reactive power drawn from the transmission line [1], [2]. The reactive power compensation can be optimally provided by fixed capacitors (FCs), static VAR compensator (SVCs) and/or synchronous motors (SMs). These equipments are widespread available along the transmission system for the voltage drop and real power loss recovery. Fixed and switching capacitors are well-known as conventional methods, but they have some mechanical problems, such as slow responses, over/under compensation and harmonics injection in line voltage and current due to step changes operation of capacitor groups [3].

This paper proposed another type of SVC called Fixed-Capacitor Thyristor Controlled Reactor (FC-TCR). The controlling signal for the thyristor is adjusted by artificial neural network method, instead of using traditional discrete load switching method. This approach increases the rapid and dynamic balancing capability of the whole system.

II. FIXED-CAPACITOR THYRISTOR CONTROLLED REACTOR (FC-TCR)

Basically, the TCR only provides continuously controllable reactive power in the lagging power-factor range. To extend the dynamic controllable range to the leading power-factor domain, a fixed-capacitor bank is shunt-connected with the TCR. The TCR MVA is rated larger than the fixed capacitor to compensate (cancel) the capacitive MVA and provide net inductive-reactive power should a lagging power-factor operation be desired. The fixed-capacitor banks which is usually connected in a star configuration are split into more than one 3-phase group. Each capacitor contains a small tuning inductor connected in series and tunes the branch to act as a filter for a specific harmonic order. For instance, one capacitor group is tuned to the 5th harmonic and another to the 7th harmonic, whereas another group is designed to act as a high-pass filter. At fundamental frequency, the tuning reactors slightly reduce the net MVA rating of the fixed capacitors [4].

An FC–TCR is usually connected to the high-voltage power system by means of a step-down coupling transformer, as shown in Fig. 1.

The compensator susceptance, BSVC, is given by (1)

\[ B_{SVC} = \frac{B_\sigma (B_C + B_{TCR})}{B_\sigma + B_C + B_{TCR}} \]  

where \( B_\sigma \) is the susceptance of the transformer and \( B_{TCR} \) is variable from 0 to \( B_L \), according to the firing angles from 180\(^\circ\) to 90\(^\circ\).

The susceptance limits can be calculated in (1). Susceptance at the production (capacitive) limit, that is, with \( B_{TCR} = 0 \) at \( \alpha = 180\(^\circ\) \), is expressed in (2). Susceptance at the absorption (inductive) limit, that is, with \( B_{TCR} = B_L \) at \( \alpha = 90\(^\circ\) \), is given by (3).

\[ B_{SVC_{\max}} = \frac{B_\sigma B_C}{B_\sigma + B_C} \]  

\[ B_{SVC_{\min}} = \frac{B_\sigma (B_C + B_L)}{B_\sigma + B_C + B_L} \]

By dimensioning the ratings of the TCR and the capacitor, respectively, the production and absorption ranges can be selected according to the system requirements. It must be...
noted that $B_L$ is a negative quantity. The total susceptance $B_{SVC}$ of the static var compensator does not change linearly with $BTCR$. However, if $(B_C/B_a) << 1$ and $(B_L/B_a) << 1$, which is usually the case, the nonlinearity is relatively small.

III. SYSTEM MODELING AND SIMULATION RESULTS

The proposed neural network based FC-TCR for reactive power compensator is shown in Fig. 2. This system consists of reactive power measurement, PC-based neural network, and FC-TCR unit.

The neural network structure is designed with four-layered network (1 input layer, 2 hidden layers and 1 output layer). The input signals are the load current ($I_L$), and the reactive power ($Q$). There are 10 and 1 nodes in the first and second hidden layers, respectively. The output variable is the firing angle of the thyristor ($\alpha$). In this structure, the biases are connected in the hidden and output layers. The activation function utilizes the tangent sigmoid transfer function (tansig) in the first hidden layer and linear transfer function in the second hidden layer. The mean square error is used as the error performance function. The Levenberg-Marquardt backpropagation learning algorithm is applied for training process.

The simulation performance was divided in three steps. The first step is the generating training data pattern. This data simulation were used for the second step of the simulation, called the training process. The training data set are load current ($I_a$), reactive power ($Q$) and the firing angle ($\alpha$). The last step was the inserting of NN block results from the training process into the proposed model.

The result of the generating data simulation is shown as in Fig. 3. The target of firing angle of thyristor is changed due to the variation in load current ($I_a$) and reactive power ($Q$).

The overall result of the proposed model includes neural network-based FC-TCR is shown as in Fig. 4. This result indicates the condition where the effect of reactive power compensation when the reactive power ($Q$) decreases to zero.

IV. CONCLUSION

This paper has effectively shown that a FC-TCR based neural network control algorithm is able to replace traditional load-switching equipment in order to improve the power system unbalance condition under reactive power reduction. The main benefits of this system are flexibility, quickness, efficiency, reliability and economy. For the time being, the proposed method has still some limitations, such as the complex structure design of the neural network, especially the numbers of layers and neurons in each layer. This problem can overcome by implementing different approach of intelligent techniques for the controlling unit of FC-TCR in the future studies.

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VI. REFERENCES