Neural Identification of Average Model of STATCOM using DNN and MLP

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***Abstract*—Modeling of STATCOM is conventionally performed in the *time-domain*. Amongst them, dq-theory is well-known in which state-space equations are used for the analysis. Power systems, however, use the *frequency-domain* information in phasor-related studies such as load flow analysis. Because *time-domain* models of FACTS controllers cannot be directly applied to the power system analysis, an intelligent model can usefully bridge the time-domain information to the corresponding frequency-domain data. This paper proposes two neural network identifiers based on the existing time-domain average model of STATCOM. Extended resultant bridge presents an average-neural model of STATCOM, which can be analytically applied to power systems. To this extent, design and development of two neural network identifiers are performed using the dynamic neural network (DNN) and the multi-layer perceptron (MLP). To verify the developed models, the exact solutions obtained from the average model of STATCOM are compared with the outcomes of the DNN and the MLP identifiers. Moreover performance of the two identifiers is accordingly compared as well.**

***Index Terms*-- DNN, FACTS controllers, MLP, modeling, neural-averaging, STATCOM.**

I. Introduction

DEREGULATED systems consider transmission lines as the principal components of the electricity market for both producers and consumers of energy. At the same time, an optimal power flow (OPF) determines the amount of energy to be transferred through each transmission line. This further helps the market to achieve a competitive pricing tool. Therefore, it is necessary to develop accurate models in order to establish a fair pricing system. In fact, if the operation of the modelled equipments is close to that of their exact devices, the energy pricing will be more accurate. In particular, this would be crucial when FACTS devices are engaged in the OPF for mitigation of congestion of transmission systems (CTS).

Typically, in [1]–[5], FACTS devices are suggested to alleviate and/or regulate the CTS. Additionally, the FACTS devices are modelled as either pure reactive elements (e.g. inductors and capacitors) or independent voltage/current sources. However, power losses of FACTS devices are *not* included in the analysis by the introduced models, assuming negligible *energy consumption* by the device itself. When the number and capacity of the employed FACTS devices increases, considerable energy losses is cancelled in power flow analysis (i.e. part of the network load is cancelled). This undermines the correctness of the process of energy pricing management.

Meanwhile, the principal objective is to bridge the instantaneous models to the power system single-frequency requirement. For example, power flow analysis is widely used in power systems in order to control active and reactive power as well as protection systems and pre-fault calculations. Moreover, deregulated power systems and the CTS control are additional applications in electricity market. This paper develops a bridging intelligent identifier that includes power losses in the analysis. Moreover, we assume an existing average model of STATCOM that is based on the well-known stat-space averaging technique [6]-[8]. The average model appropriately takes into account the low-frequency variations of the DC–link of the converter as well as the power losses related to the AC-side. It should be noted that the switches are treated as ideal.

However, one issue concerned with this model is that for each switching period a considerable number of differential equations have to be solved. This depends on the switching frequency, and takes long to process the OPF. To remedy this issue, the neural network modelling technique is employed to link the instantaneous outcomes of the STATCOM to the single–frequency power system analysis. The developed model produces power losses as well as angles and magnitudes that are suitable for phasor analysis in steady-states. Here it is examined two identifiers; the dynamic neural network (DNN) and the multi-layer perceptron (MLP). The objective is to compare the accuracy and reliability of the two identifiers. In this paper the developed model is called *average–neutral (AN)* model of STATCOM.

II. Average Model

Averaging technique is a common approach to the modeling of power converters. Switch-mode converters have a discontinuous behavior, which is very complex in analysis. Average modeling approximates the behavior of the converter from a periodic discontinuous system to a periodic continuous one, maintaining smooth waveforms by removing high order harmonics. Average model of STATCOM is presented in [6], shown here by Fig. 1(a).

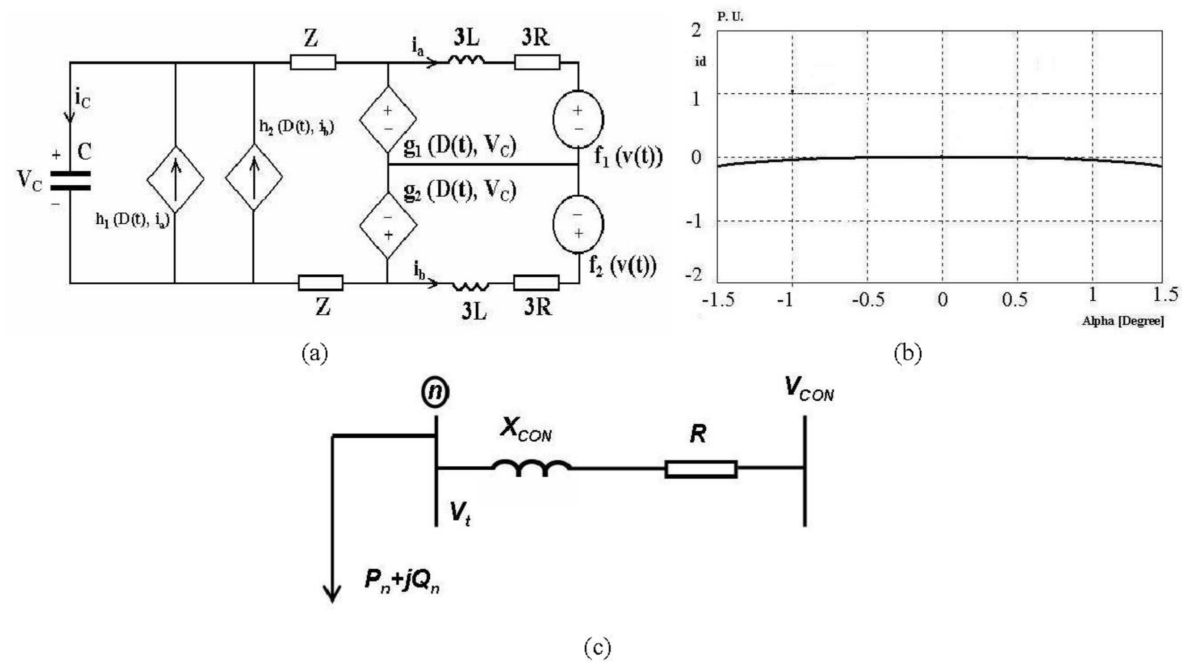


Figure 1: (a) Average circuit model of STATCOM, (b) typical internal power losses of STATCOM obtained by the average model, and (c) adaptation of the average model connected to the power system by adding a bus for STATCOM.

In this model, L introduces the equivalent coupling inductance between the converter and the power system. The resistance R is part of the compensator losses related to the interconnection of the converter to the power system. The other part of the power losses corresponds to the converter losses that are absorbed by the proper modulation of the converter switches. Fig. 1(b) shows typical STATCOM power losses in P.U. against the phase shift between the converter output and the power system voltage (α) that is obtained by the average model.

While the average model presents a time-dependent circuit, a PQ or PV model is essential for the power flow analysis. Hence, here it is performed adaptive analysis to get the supplied active and reactive powers of STATCOM (P_{CON} and Q_{CON}). A new bus is added for every STATCOM as the converter AC voltage, which is connected to an existing bus n through the commutation reactance (X_{CON}) and the AC resistance (R).

III. Identification of STATCOM Model using Neural Network

Average model of Fig. 1(a) describes a state-space model in a circuit format, which solving differential equations will lead eventually to a steady-state solution. Meanwhile, moving from one steady state to another takes time to complete the transient regime that is not suitable for the OPF. An OPF program seeks among the feasible region for a desirable solution. Thus, it is necessary for the OPF to be performed as fast as possible. One approach to achieve a fast OPF is the identification of the average model of STATCOM using the neural network. The average model is analyzed as a reference to generate required training data for the *average-neural model (AN)*.

Training data can be produced in two steps. First, Fig. 1(a) is assumed as the exact model suggested in [6]. Then, to cover operating range of STATCOM, magnitude of the terminal voltage is varied within $|V_t| \in [0.7, 1.2]$ P.U. by small steps (e.g. 0.01 P.U. (see Fig. 1(c))). Also, the phase angle between the converter voltage V_{CON} and the terminal voltage V_t ($\angle(V_{CON}, V_t)$) is varied within $\alpha \in [-1.5^\circ, 1.5^\circ]$ by small steps (e.g. 0.01°). For the given small steps, total number of operating points sums up to 15000 set of steady-state training data for the STATCOM.

Second, for every operating point, the *time–domain* model of Fig. 1(a) is solved. Then, the steady-state phasors are obtained from the instantaneous solution. This is used to calculate and store the absorbing active as well as generating/absorbing reactive powers of STATCOM delivered to bus n. Gathering all the calculated data leads to formation of a database for single-frequency operation of STATCOM in power system.

The next step will be the study and selection of a suitable neural network identifier for the average model

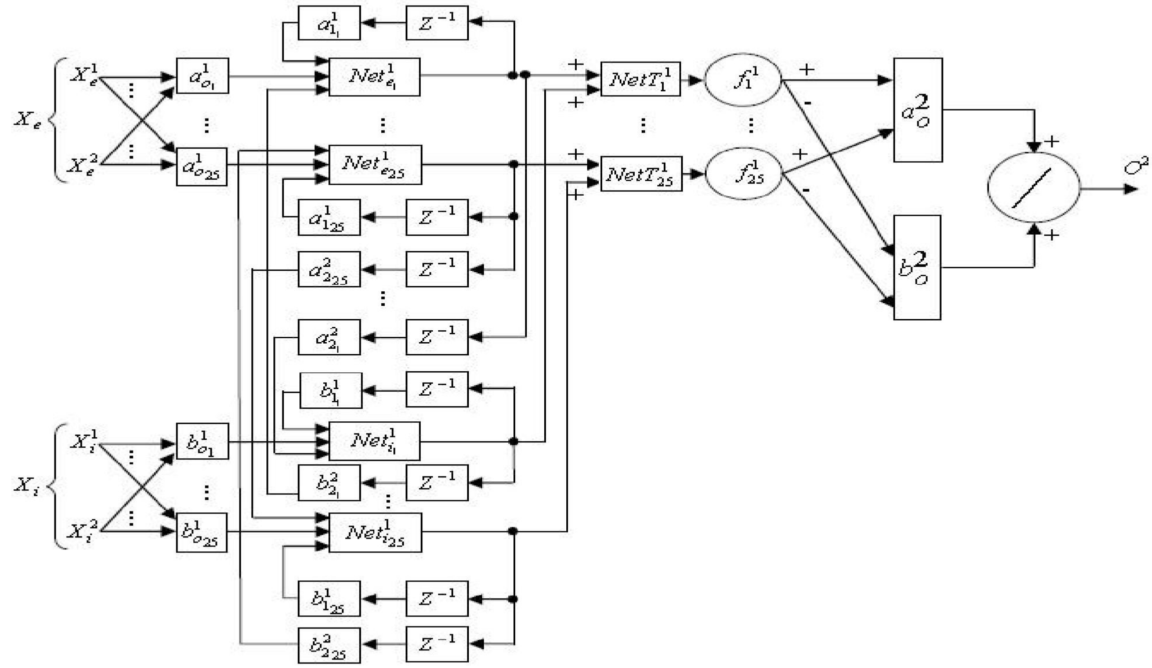
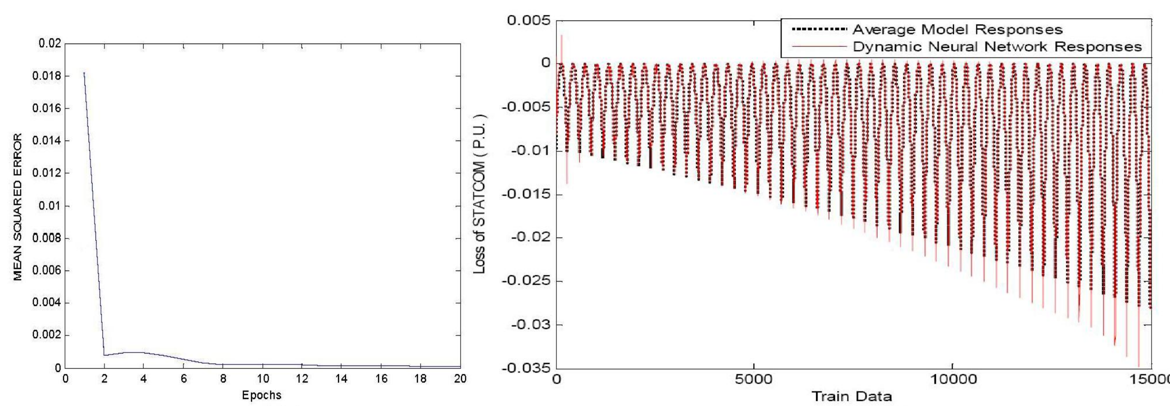


Figure 2: The structure of the DNN that is designed to identify the average model of STATCOM.



(a) (b)

Figure 3: (a) Mean squared error of the trained data, (b) The output (power losses) of the DNN AN together with the exact output of average model for 15000 trained data.

of Fig. 1(a). Here we identify the average model of STATCOM by two well-known neural network identifiers, dynamic neural network (*DNN*) and multi-layer perceptron (*MLP*). It is noticeable that other identifiers should also be investigated that is left for future studies. Outcomes of the *AN* identifiers of STATCOM are then correspondingly compared.

A. The DNN neural identifier

There are various structures for the dynamic neural network. The employed structure for identifying the AN model is given by Fig. 2 in which the DNN includes two layers. The hidden layer has delay blocks taken from the neurons, which take the data history of the network into account for the progressing output. Index *e* corresponds to the exhibitory positive classes (e.g. positive input vector $\mathbf{X_e}$), and index *i* relates to inhibitory negative classes (e.g. negative input vector $\mathbf{X_i}$). Each neuron from the exhibitory class has a delayed input from its corresponding neuron in inhibitory class and vice versa. Output of each neuron is applied to a non-linear neuron activation function to be able to model non-linear systems.

Then, the outcomes of the activation functions are weighted by $\mathbf{a_o^2}$ for exhibitory classes, and by $\mathbf{b_o^2}$ for inhibitory classes. These weighted productions are eventually applied to the linear activation function of the output layer to get the output of the DNN. The advantages of the DNN are non-linear modelling capability as well as the fast network convergence

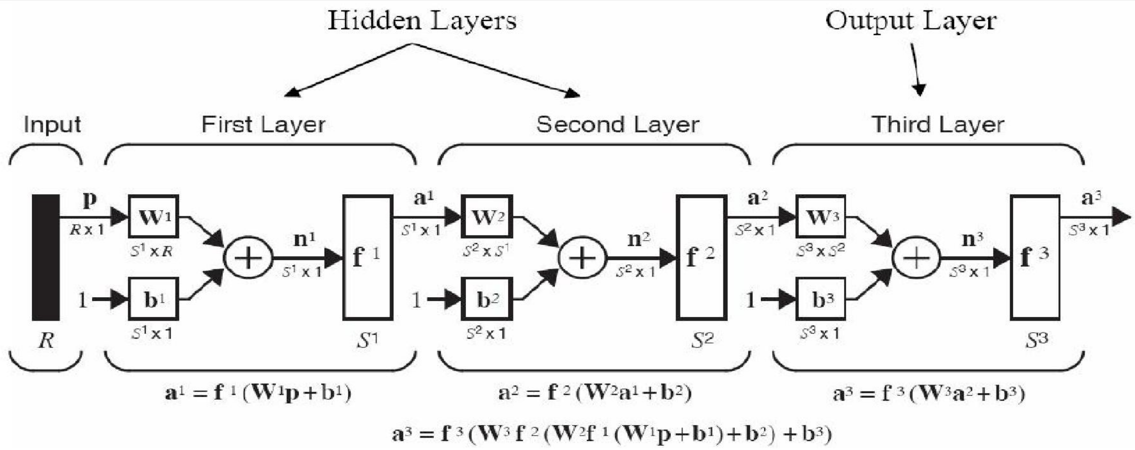
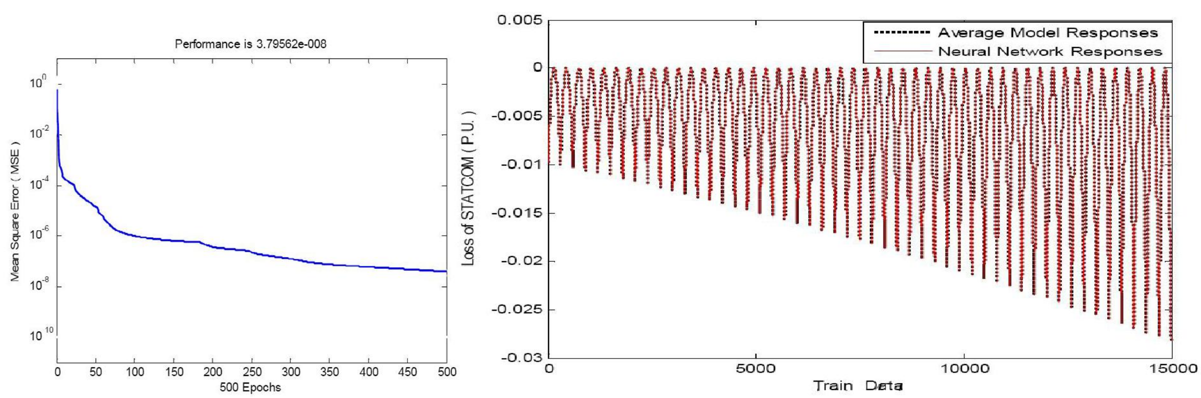


Figure 4: (a) The structure of the designed MLP neural network to identify the average model of STATCOM.



(a) (b)

Figure 5: (a) Mean squared error of the trained data, (b) The output (power losses) of the MLP AN together with the exact output of average model for 15000 trained data

because of the inherit delays of the structure. The following relationships describe the designed feed forward state of the network:

$$\begin{cases} \mathbf{X_e} = [X_e^1, X_e^2]^t \\ \mathbf{X_i} = [X_i^1, X_i^2]^t \end{cases} \qquad (1)$$

$$Net^1_{e_j}(t) = a^1_{o_j} X_e(t) + a^1_{1_j} Net^1_{e_j}(t-1) - b^1_{2_j} Net^1_{i_j}(t-1) \qquad (2)$$

$$Net^1_{i_j}(t) = b^1_{o_j} X_i(t) + b^1_{1_j} Net^1_{i_j}(t-1) - a^1_{2_j} Net^1_{e_j}(t-1) \qquad (3)$$

$$NetT^1_j(t) = Net^1_{e_j}(t) + Net^1_{i_j}(t) \qquad (4)$$

$$O^1_j(t) = f^1_j(t) = \frac{1-e^{-NetT^1_j(t).k}}{1+e^{-NetT^1_j(t).k}} \qquad (5)$$

All parameters of the network are trained using the back propagation method, and the structure is designed by trial end error. In this research, different structures were examined in which 25 neurons is considered for the hidden layer alongside with one neuron for the output layer.

Designed structure of Fig. 2 is simulated with MATLAB, where Fig. 3(a) shows the reduction in mean squared error of the training data, Fig. 3(b) depicts the output of the DNN as well as the power losses analysed by the average model, and details of zooming Fig. 3(b) for various terminal voltages over $\alpha \in [-1.5^\circ, 1.5^\circ]$ will be presented in the full paper. Simulation results indicate that the AN model of STATCOM, developed by the DNN, introduces the mean squared error of 0.12% and mean error of 0.3775% for the trained data. This situation confirms that the DNN is unable to develop successfully the *AN* model of STATCOM because the DNN uses the history of the response to identify the progressing output.

B. The AN model using the MLP

The MLP neural network is a global estimator, which an initial processing on training data is taken place followed by designing its structure for the AN model. Structure of this design is shown by Fig. 4, where three hidden layers are proposed for the MLP neural network. By examining and performing various tests, eight neurons are considered for the first and the second layers and one neuron for the third layer. Neuron functions of the first and the second layers are considered identical as follows:

$$f^1(n) = f^2(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \quad (6)$$

Also, weighting matrices of the three layers are $\mathbf{W^1}$, $\mathbf{W^2}$ and $\mathbf{W^3}$, and the 2×1 input vector $\mathbf{P}$ includes the terminal voltage and injected reactive power of STATCOM to bus n as shown by Fig. 1(c). Three vectors $\mathbf{b^1}$, $\mathbf{b^2}$ and $\mathbf{b^3}$ are the threshold values of the neurons, and three outputs of the three layers are $\mathbf{a^1}$, $\mathbf{a^2}$ and $\mathbf{a^3}$.

To train this network, again 15000 operating states are used. Figure 9(a) demonstrates the reduction of the mean squared error during the training process, and Fig. 5(b) gives the response of the MLP *AN* model to these trained data alongside with the exact power losses of the average model. Simulation results show that when the AN model of STATCOM is identified by the MLP, then the error between the average and the AN models is considerably low. The mean error is equal to 0.0147%, and the mean squared error is 0.000003795%. Hence, the MLP identifies the average model with an acceptable error, much lower compared to the DNN.

IV. Conclusion

Average model of STATCOM describe its exact operation, while high frequency ripples are ignored. This model can be used for steady state analysis of power systems such as load flow program. However, an identifier is needed to bridge the time domain average model to the frequency domain power system analysis. This paper aims at doing this objective by designing two neural network identifiers; the dynamic neural network (DNN) and the multi-layer perceptron (MLP). These neural networks are trained using up to 15000 steady state operating data that are obtained by simulating the average model of STATCOM. Outcomes of the two identifiers are compared with the exact solutions of the average model. The results show that the MLP provides much more accurate outcomes compared to the DNN. Therefore, the MLP identifier can be applied to the power system planning and analysis purposes.

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