# Neural Network Modeling of STATCOM Using the GAMMA and the RBF Identifiers

M. Tavakoli Bina, *Senior Member, IEEE*, and S. Rahimzadeh

*Abstract*—Analysis of power systems is carried out in *frequency-domain* (e.g. load flow studies). Currently FACTS controllers are included in the analysis, whereas power electronic-based devices are modelled in the *time-domain* using state-space equations (e.g. STATCOM). Since these models cannot be directly used for power system analysis, it is necessary to seek suitable alternatives that are applicable to the *frequency-domain* analysis. Average model of STATCOM is a *time-domain* representation in which high frequency switching ripples are vanished. This paper extends existing average model, and presents an *average-neural* model of STATCOM to bridge the time and frequency domains analysis. Thus, development of two identifier neural networks is studied, namely Gamma and radial basis function (RBF). Then, these two models are compared with their exact solutions in terms of the least average error. Selected average-neural model is then used as an application in the 14-bus IEEE power system to verify the usefulness of the suggested model for power system studies.

*Index Terms*—FACTS controllers, STATCOM, Modeling, Averaging, GAMMA, RBF.

## I. INTRODUCTION

TRANSMISSION systems are emerged as highways for both producers and consumers in the restructured power industries. Models of the employed power electronics devices are used in optimal power flow (OPF), which further helps achieving a pricing tool for a competitive electricity market. Therefore, the more accurate are the developed models, the fairer pricing system is established. In fact, if electrical devices are modelled close to their exact operation, the energy pricing will be more precise. In particular, this would be more crucial when FACTS devices are engaged in the OPF to control the congestion of transmission systems (CTS).

Typically, FACTS devices are suggested in [1]–[5] to regulate the CTS. Additionally, the FACTS controllers are usually modelled like pure reactive elements (e.g. inductors and capacitors) or independent voltage/current sources. However, power losses of FACTS devices are *not* taken into account by the introduced models, ignoring the *consumed energy* by the device itself. When the number and capacity of the employed FACTS devices increases, considerable energy losses are cancelled in the power flow analysis (i.e. part of the network's load is cancelled). This undermines the accuracy of process of energy pricing management.

This paper develops a proper model of STATCOM to be used in those power system applications that determine their steady-state operating condition by means of the power flow analysis (e.g. applying the FACTS controllers to active and reactive power control, protection and pre-fault calculations, deregulated power systems and the CTS control purposes in electricity market). The proposed model considers power losses of the static controller in the analysis using an average technique for modelling of STATCOM, presenting an instantaneous *time–domain* model [6]. The average model appropriately takes all aspects into account including the DC–link voltage of the converter as well as the power losses. However, the problem with this model is that it is necessary to solve a set of differential equations for every operating condition; this slow process is a drawback for the OPF. To remedy this issue, a neural network model is suggested for linking the instantaneous outcomes of the STATCOM to the single–frequency power system analysis. The resultant model produces the required PQ–phasor that is suitable for power system steady state analysis. Here it is examined both the GAMMA and the RBF identifier neural networks to select the most accurate and reliable one. In this paper, the developed model is called *average–neural (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 analytically very complex. Average modeling approximates the behavior of the converter from a periodic discontinuous system to a periodic continuous one, producing smooth waveforms by removing high order harmonics. Average model of STATCOM is presented in [6], shown here by Fig. 1(a). 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 concerned with 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 ($\alpha$) that is obtained by the average model.

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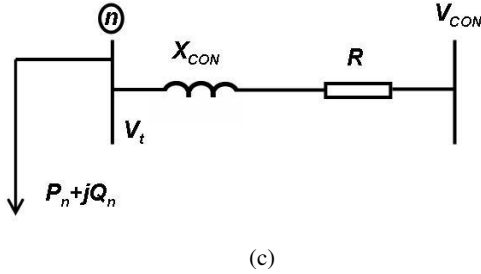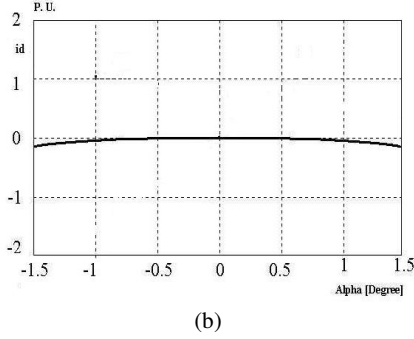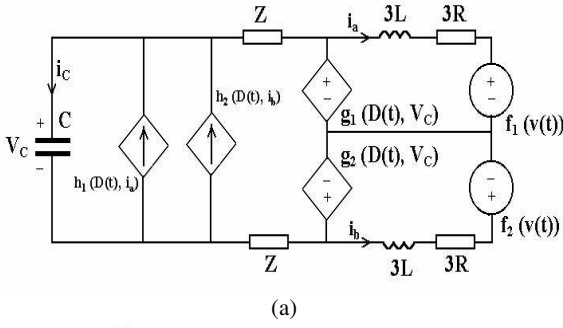
(a)



(b)



(c)

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 new bus for STATCOM.

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 each STATCOM as the AC voltage of the converter, which is connected to an existing bus $n$ through the commutation reactance ($X_{CON}$) and the AC resistance ($R$). Ignoring $R$ for big $X_{CON}/R$ ratios, the active and reactive powers of the compensator can be obtained by the well-known power relationships for two buses that are connected through an inductive reactance:

$$\begin{cases} P_{CON} = \dfrac{V_t V_{CON}}{X_{CON}} \sin(\alpha - \dfrac{\pi}{M}) \\ Q_{CON} = \dfrac{V_t}{X_{CON}} (V_{CON} - V_t \cos(\alpha - \dfrac{\pi}{M})) \end{cases} \quad (1)$$

Where $|V_t|$ and $|V_{CON}|$ are the magnitudes of the fundamental voltages of the bus $n$ and AC bus of the converter, respectively. Fig. 1(c) describes the power flow model, including the above parameters. Also, $P_n$ and $Q_n$ are active and reactive powers of the power system at bus $n$.

III. IDENTIFICATION OF THE AN MODEL

Average model of Fig. 1(a) describes a state-space model in a circuit format. Analyzing this circuit leads eventually to a steady-state solution. Meanwhile, moving from one steady-state to another is lengthy in transient regimes; this is not suitable for the OPF. An OPF program has to seek one point amongst all feasible operating points, where high speed analysis is essentially needed to boost its performance. One approach to overcome this issue could be identification of the average model of STATCOM by a neural network. The average model as a reference can generate required training data for the *average-neural model (AN)*. Training data can be produced as follows:

- Assume Fig. 1(a) as the basic model suggested in [6]. 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 of 0.01 P.U. (see Fig. 1(c)). Also, the phase angle between $V_{CON}$ and $V_t$ ($\angle(V_{CON}, V_t)$) is varied within $\alpha \in [-1.5°, 1.5°]$ by steps of $0.01°$. Thus, the total number of operating points is summated up to 15000 set of steady-state training data for STATCOM.

- For every operating point, the *time–domain* model of Fig. 1(a) is solved to reach steady-state solution. Then, this is used to calculate and store the absorbing active as well as generating/absorbing reactive powers of STATCOM delivered to bus $n$. This leads to construction of a database for the STATCOM operating phasors.

The next step would be the selection of a suitable neural network to identify the average model of Fig. 1(a). Here we identify the average model of STATCOM by two well-known neural networks of *GAMMA* and radial basis function (*RBF*), while dynamic neural network (*DNN*) and multi-layer perceptron (*MLP*) can be examined though. The best solution is then introduced as the AN identifier of STATCOM.

A. *The GAMMA neural network identifier*

Figure 2 presents the designed GAMMA neural network for the average model, having two inputs and one output.
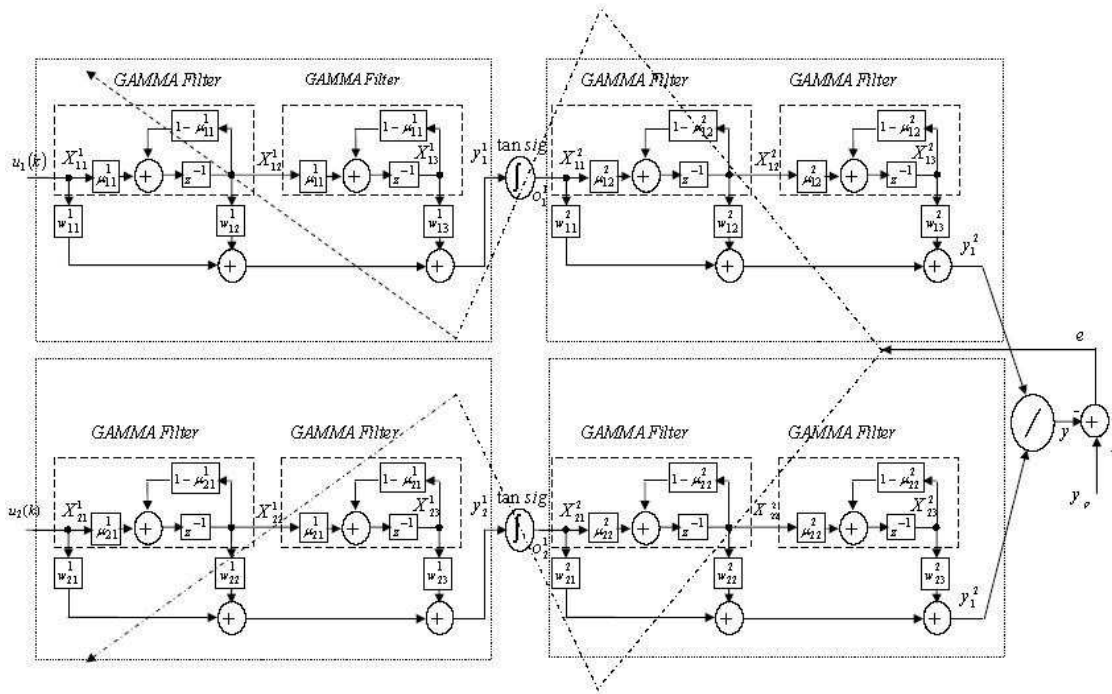
Figure 2: The designed structure of the GAMMA neural network.

This designed network includes an input layer, a hidden layer with non-linear neuron functions along with a linear function output layer. Memory size of the GAMMA is determined by the parameter $\mu$. The inputs $u_1$ and $u_2$ are separately multiplied by $\mu$, and then passed through a delay block $Z^{-1}$ to arrange memory or filter for the neural network (blocks $\mu$, $Z^{-1}$ and $1-\mu$). Every synapse of the GAMMA network may contain more than one filter, which needs to be determined by designing the structure of the neural network. The lower is the parameter $\mu$, the history of the neural network influences more effectively the generation of the progressing output. Furthermore, synapses may have several weighting factors to improve the capability of modelling non-linear systems. To show the performance of this neural network, the feedforward calculation using the parameters of Fig. 2 is presented as follows:

$$X_{i1}^1(t) = u_i(t) \tag{2}$$

$$X_{i2}^1(t) = \left(1 - \mu_{i1}^1\right) X_{i2}^1(t-1) + \mu_{i1}^1 X_{i1}^1(t-1) \tag{3}$$

$$X_{i3}^1(t) = \left(1 - \mu_{i1}^1\right) X_{i3}^1(t-1) + \mu_{i1}^1 X_{i2}^1(t-1) \tag{4}$$

$$y_i^1(t) = \sum_{j=1}^{3} w_{ij}^1 X_{ij}^1 \tag{5}$$

$$o_i^1(t) = \tan sig\left(y_i^1(t)\right) \tag{6}$$

$$X_{i1}^2(t) = o_i^1(t) \tag{7}$$

$$X_{i2}^2(t) = \left(1 - \mu_{i2}^2\right) X_{i2}^2(t-1) + \mu_{i2}^2 X_{i1}^2(t-1) \tag{8}$$

$$X_{i3}^2(t) = \left(1 - \mu_{i2}^2\right) X_{i3}^2(t-1) + \mu_{i2}^2 X_{i2}^2(t-1) \tag{9}$$

$$y_i^2(t) = \sum_{j=1}^{3} w_{ij}^2 X_{ij}^2 \tag{10}$$

$$y(t) = \sum_{i=1}^{2} y_i^2(t) \tag{11}$$

Where the superscript indexes indicate the layer number, the first subscript indexes show the neuron number and the second one introduces the filter number, $y$ is the output of each layer, and $w$ is the weighting factor. The training of the above network can be performed using the back propagation method.

Various structures of the GAMMA neural network were examined in this research. Amongst them, a two–layer structure provides the lowest error for the average model of STATCOM. Each layer includes 30 GAMMA filters with identical parameters $\mu = 0.9$. Also, the inputs $u_1$ and $u_2$ are $V_t$ and reactive power injected to the bus $n$ (see Fig. 1(c)), and the output $y$ is the power losses of STATCOM. Figure 3(a) shows the reduction of mean squared error (MSE) of the trained data, and Fig. 3(b) depicts the output $y$ (power losses)

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along with the exact power losses analyzed by the average model. By increasing $|V_t|$, the absorbed power losses of STATCOM is also increased.

To examine the capability of the GAMMA network to identify the AN model, Figs. 3(c)–(d) zoom in the Fig. 3(b) for two terminal voltages over $\alpha \in [-1.5°, 1.5°]$; $|V_t| = 0.7$ P.U. and $|V_t| = 1.0$ P.U. The exact power losses taken from the average model conform to those of Fig. 1(b) that is reported in [6] and simulated here for this research. The GAMMA neural network response corresponds to the output of the developed *AN* model. The mean error is equal to 1.9607%, and the mean squared error is 0.12%. It can be seen that the identification of the average model by the GAMMA neural network differs from that of the exact response, providing some unacceptable results. Specifically, the initial trained data introduce bigger errors compared to those of the final errors, because the GAMMA neural network needs the history of operation of STATCOM.

*B. The RBF neural network identifier*

The designed RBF neural network is illustrated by Fig. 4, having two input vectors ($\mathbf{X}$) and one output ($y$). The inputs are applied directly to the neurons with Gaussian activation functions as follows:

$$\begin{cases} \Phi_i(r_i) = e^{\frac{r_i^2}{2\sigma_i^2}} \\ r_i = \|\mathbf{X} - \mathbf{t_i}\| \end{cases} \text{ where } \begin{cases} \sigma_i > 0, \quad i = 1,2,\ldots,m \\ \mathbf{X} = [x_1, x_2, \ldots, x_m]^\bullet \end{cases} \quad (12)$$

Where $\mathbf{t_i}$ and $\sigma_i$ are the centre and spread of the Gaussian function $\Phi_i$, and $r_i$ is the Euclidean distance of $\mathbf{X}$ from $\mathbf{t_i}$. The output $y$ of the designed neural network can be given by applying thirteen weighting factors ($w_i$ for $i = 1,2,\ldots,13$) to the activation functions:

$$y = \sum_{i=1}^{13} w_i \Phi_i(\|\mathbf{X} - \mathbf{t}_i\|) \quad (13)$$

To classify the data of the average model of STATCOM, the Euclidean distance of all 15000 training data from each other are needed to be calculated and stored. This necessitates huge memory space for the neural network, forcing the program to double the steps of $|V_t|$ as well as $\alpha$. This lowers the number of training data to 7500 that is further selected 4000 data set. The number of neurons of the hidden layer is set to 13 by trial and error, which is exactly equal to the number of voltage steps in the 4000 chosen training data. The spread of Gaussian functions is designed to be equal to two.
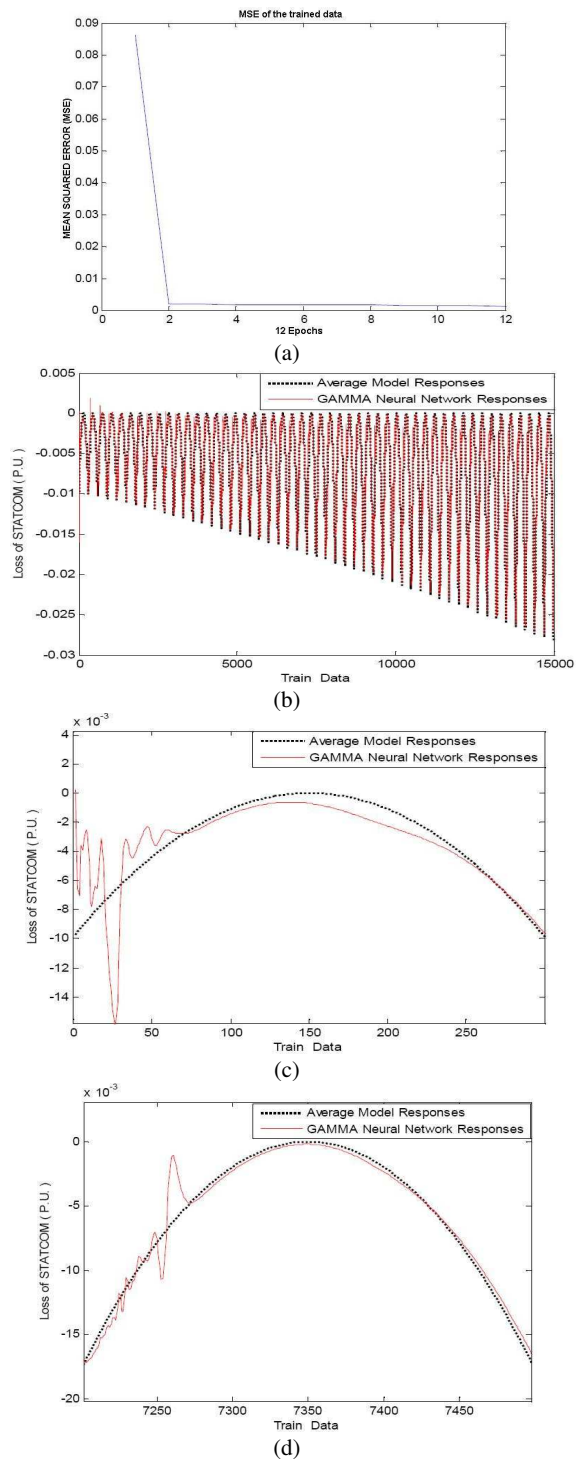

(a)


(b)


(c)


(d)

Figure 3: (a) The MSE of the trained data, (b) Power losses of the GAMMA identifier together with the exact output of average model for 15000 trained data, (c)–(d) The output of STATCOM over $\alpha \in [-1.5°, 1.5°]$ when $|V_t| = 0.7$ P.U. and $|V_t| = 1.0$ P.U., respectively.
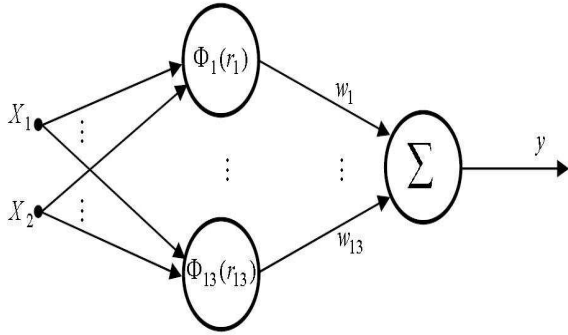
Figure 4: Designed schematic structure of the RBF neural network to identify averaged model of STATCOM.

Figure 5(a) shows total squared error of the training data, where the mean error and mean squared error are equal to 0.1043% and 0.058% respectively, and Fig. 5(b) illustrates the response of the RBF neural network as well as the power losses of STATCOM produced by the average model for 4000 chosen steady state operating conditions. To discuss the suitability of the RBF for the *AN* model, Figs. 5(c)–(d) zoom in the Fig. 5(b) for two terminal voltages over $\alpha \in [-1.5^{\circ}, 1.5^{\circ}]$; $|V_t| = 0.7$ P.U. and $|V_t| = 1.0$ P.U. Curves of power losses of STATCOM correspond to the exact average model together with the RBF *AN* model, both simulated with MATLAB. The results confirm that the accuracy of the RBF *AN* model is much higher than that of the GAMMA neural network. Nevertheless, one issue could be the reduction of number of the training data that affects the precision of the RBF *AN* model.

Table I summarizes the advantages of the two designed neural network identifiers as well as their disadvantages. This makes it easier to compare the GAMMA with the RBF as identifiers of the average model of STATCOM. It should be noted, however, that the error of the RBF method is calculated for 4000 trained data whereas the GAMMA identifier takes 15000 trained data into account.

TABLE I
OVERALL COMPARISON OF THE AN IDENTIFIERS OF STATCOM.

| Neural Network Identifier | Mean Squared Error (%) | Mean Error (%) | Number of Trained Data |
|---|---|---|---|
| *GAMMA* | 0.12 | 1.9607 | 15000 |
| *RBF* | 0.058 | 0.1043 | 4000 |

## IV. CONCLUSION

Averaging modeling approximates a discontinuous complex system to a simple continuous structure, preserving the original characteristics such as DC-link voltage variations related to power losses and modulation index. Thus, the average model of STATCOM is more suitable for power
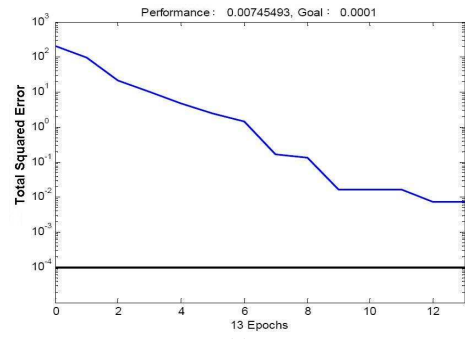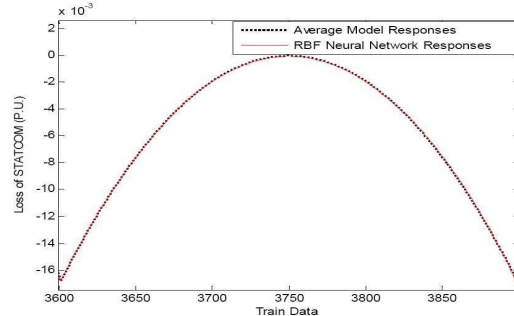


(a)
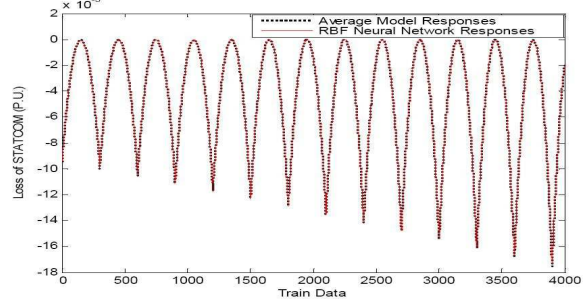


(b)
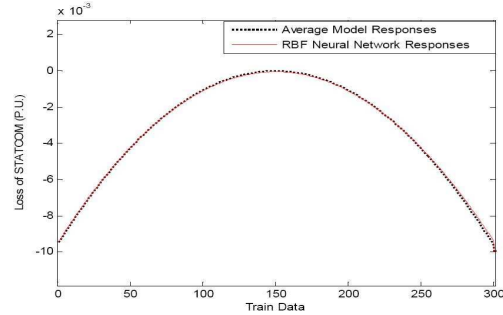


(c)



(d)

Figure 5: (a) Total squared error of the trained data, (b) The output (power losses) of the RBF AN together with the exact output of average model for 4000 trained data, (c)–(d) The output of STATCOM over $\alpha \in [-1.5^{\circ}, 1.5^{\circ}]$ when $|V_t| = 0.7$ P.U. and $|V_t| = 1.0$ P.U., respectively.

system analysis (e.g. the OPF) compared to its conventional

simple capacitive/inductive model. This paper considers the previously introduced average model of STATCOM in the time domain. It is proposed that the time domain variables can be treated using the neural network identifier to achieve frequency domain power system phasors. Hence, the GAMMA and the RBF neural networks are used to identify the STATCOM in steady stales. These two networks are trained using simulation of the average model up to 15000 steady-state operating conditions. Further, outcomes of the developed *AN* models are compared with simulations of the exact average model. Then, advantages as well as disadvantages of both identifiers are examined, and the resultant errors are compared.

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## VI. BIOGRAPHIES



**M. Tavakoli Bina** was born in Tehran, Iran, on July 14, 1962. He received a B.Sc. degree from the University of Teheran in 1992, and his Ph.D. degree in power electronics and power system interconnection from the University of Surrey in the UK in June 2001. He has been an IEEE member for six years. He is presently holding an associate professor position at the K. N. Toosi University of Technology, researching in the area of designing power electronics devices as well as power system analysis. His latest work corresponds to the design and installation of a research Laboratory in the area of power electronics multilevel converters and FACTS devices.



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