Efficient Reconfigurable Microstrip Patch Antenna Modeling Exploiting Knowledge Based Artificial Neural Networks

Murat Simsek and Ashrf Aoad

Abstract Artificial neural network (ANN) is widely used for modeling and optimization in antenna design problems. It is a very convenient alternative for using computationally intensive 3D-Electromagnetic (EM) simulation in design. The reconfigurable microstrip patch antennas have been considered to ensure operational frequencies for different kind of purposes. ANN is used for modeling of antenna design problems to obtain a surrogate based model instead of a computationally intensive 3D-EM simulation. Further improvement in modeling, a prior knowledge about the problem such as an empirical formula, an equivalent circuit model, and a semi-analytical equation is directly embedded in ANN structure through a knowledge based modeling technique. Knowledge based techniques are developed to improve some properties of conventional ANN modeling such as accuracy and data requirement. All these improvements ensure better accuracy compared to conventional ANN modeling. The necessary knowledge can be obtained by the coarse model which is a complex 3D-EM simulation in terms of grid size selection. Knowledge based techniques can improve the performance of conventional ANN through the guidance of the coarse model. As long as the coarse model approximates to the computationally intensive 3D-EM simulation, the performance of the knowledge based surrogate model can converge to the design targets. The efficiency of modeling strategies is demonstrated by a reconfigurable 5-fingers microstrip patch antenna. The antenna has four modes of operation, which are controlled by two PIN diode switches with ON/OFF states, and it resonates at multiple frequencies between 1 and 7 GHz. The number of training data is changed in terms of selected parameters from the design space. Three different sets are used to show modeling performance according to the size of training data. The simulation results show that knowledge based neural networks ensure considerable savings in computational costs as compared to the computationally intensive 3D-EM simulation while maintaining the accuracy of the fine model.

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1 Introduction

Over the years, several numerical and analytical methods that employ detailed electromagnetic models of active/passive components have been developed for designing antennas. However, these methods come with their own set of limitations such as high computational cost and memory requirements. To overcome these challenges, artificial neural network (ANN) has been used as efficient alternative to conventional methods in RF and microwave modeling [23]. Several studies have been carried out for designing antennas using ANN. In the context of reconfigurable antennas, neural network was recently used as an optimization technique to activate the switches in order to realize a given reconfiguration state (e.g., resonating at certain frequency bands) [5, 10].

ANN has been extensively preferred as a modeling technique to obtain a surrogate model instead of a fine model which has high computational burden. Surrogate based modeling [20] is required to overcome this computational burden of the fine model. Surrogate based models can be fundamentally developed in two ways. First way only requires input or output mapping without any change in the computationally cheap coarse model. Space mapping based modeling [3, 9, 14, 16–18] is developed considering this approach. Second way is based on updating the coarse model during modeling process for the coarse model. ANN is very convenient to obtain this kind of coarse model.

ANN provides an efficient strategy to solve modeling and optimization problems which are essential in engineering design where only input–output data are available instead of mathematical formulations [4, 7, 11, 23, 24]. ANN modeling is generally used to construct a mapping from the input to the output depending on the data obtained from detailed physical/EM simulation models or measurements (fine model) and generate approximate results depending on some tunable parameters such as training set, topological structure, and complexity of the fine model.

Since ANN technique constitutes input–output mapping highly depending on the training set, when the points outside of the training range (extrapolation) are used as inputs for the final model after training process, responses of the model are probably unsatisfactory compared to the points inside of the training set (interpolation). ANN and the existing knowledge about the fine model should be combined in the same modeling process in order to reduce complexity of the fine model, while improving extrapolation performance or lowering data requirements for training process.

In some cases, modeling involves numerous training data to satisfy specific design purposes such as good accuracy, better extrapolation, and less computational burden. However training process takes longer time and modeling accuracy cannot be good enough with respect to design purposes. To overcome this problem, knowledge based ANN (KBANN) techniques emerged to generate an efficient model. Knowledge based modeling techniques have been developed to embed existing knowledge into the conventional ANN modeling [6, 14, 15, 19, 23]. Knowledge based models utilize less training data as compared to the conventional ANN. The knowledge provides coarse information for modeling and ANN completes rest of the information using less training data. This modeling approach provides more accuracy and better extrapolation performance than ANN models and offers less computational burden compared to the detailed physical/EM simulation models.

Knowledge based models are applied to reconfigurable 5-fingers microstrip patch antenna using ANNs in this chapter. Source difference (SD), prior knowledge input (PKI), and prior knowledge input with difference (PKI-D) [12, 14, 15, 19] methods are considered as knowledge based neural networks. Employing fine and coarse models in order to train the networks enables to develop fast and accurate EM-ANN models. The developed antenna has four modes of operation, which are controlled by two PIN diode switches with ON/OFF states, and it resonates at multiple frequencies between 1 and 7 GHz. The antenna has several attractive features such as reconfigurability, small size, and low cost. This example handles the increasing requests for the continuing application of ANN in the reconfigurable microstrip antenna design: reduction of model development cost and improving the accuracy.

Conventional ANN modeling and knowledge based modeling techniques will be presented in Section 2 and 3. Design of reconfigurable 5-fingers microstrip patch antenna will be presented in Section 4. Three different cases such as ON–ON, ON–OFF, and OFF–OFF will be handled with three training sets which have different number of samples in Section 4. Simulation results demonstrate considerable savings in computational costs as compared to the 3D-EM simulation results obtained by CST while maintaining the same level of accuracy as the 3D-EM simulation.

2 Conventional ANN Modeling Concept

ANN has been used as an important technique in engineering modeling and optimization. ANN has been widely preferred for modeling purposes in many disciplines such as function approximation, pattern recognition, signal processing, microwave design, and so on [14, 23]. The main reason for ANN being so popular among other modeling techniques is that ANN needs only input–output information obtained from the detailed physical/EM simulation models. ANN usually involves some necessary steps during training such as scaling, initialization of weight coefficients, calculating error which is used for updating weight coefficients. The main purpose of the training process is to reduce the error value as given in Fig. 1, and to increase the generalization capability of the ANN model. Weight coefficients can be obtained by the optimization process defined as

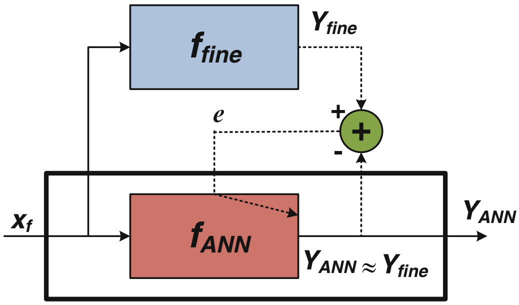

Fig. 1 The training process (updating weight coefficients in terms of error values) and the final model of the conventional ANN technique

$$w^* = \arg\min_w \left\| \cdots e^{(i)T} \cdots \right\| \qquad i = 1, 2, \ldots, N \tag{1}$$

where w indicates weight coefficient of the ANN model and N indicates the number of training data. i represents which training data is evaluated by the training process. The error term in (1) can be defined as

$$e^{(i)} = f_{fine}\left(x_f^{(i)}\right) - f_{ANN}\left(x_f^{(i)}\right) \tag{2}$$

where f_{fine} and f_{ANN} indicate the fine model and the ANN model responses, respectively. x_f indicates input of the problem. After the training process of the ANN model, the final response of the ANN model can be given by

$$Y_{ANN} = f_{ANN}\left(x_f\right). \tag{3}$$

Since generalization of ANN is mostly determined by training data set, after the training process the ANN model can generate response in terms of this data set. Extrapolation data are selected differently than training data that's why ANN response will not be highly accurate as interpolation data. The problem specific knowledge based on experience with respect to the engineering problem is required to reduce the data dependency of the conventional ANN.

3 Fundamentals of Knowledge Based Modeling Technique

In engineering design problems, an accurate model for a wide application interval can be obtained by a detailed physical/EM simulation model but it is highly nonlinear and complex, so it is called fine model that has computationally intensive mathematical expressions. In contrast, a less accurate and less computationally intensive model can be utilized instead of the fine model for modeling and optimization purposes, so it is called coarse model that has computationally less complex mathematical expressions than the fine model.

Surrogate based modeling and optimization has been developed to dispose the computational burden of the fine model exploiting a coarse model. In design optimization, the coarse model is used for the optimization process to find optimum design parameters satisfying the design purpose. But the convergence of the optimization process is directly effected by the accuracy of the coarse model. When the coarse model generates quite similar response compared to the fine model response, convergence is probably ensured during surrogate based optimization process.

The knowledge based ANN (KBANN) has emerged to fulfill the requirement for a more accurate model generation than the conventional ANN. The KBANN techniques can create new model exploiting coarse model and this new model can perform better accuracy and improve the generalization capability for interpolation and extrapolation data. The key idea behind the success of the KBANN techniques is that the more accuracy that is needed the more knowledge from the problem space has to be obtained by the coarse model. Another way to overcome the need for more knowledge instead of using the coarse model is to have more training data which requires more effort for data generation.

3.1 Source Difference Method

The source difference method [21, 22] is one of the earliest methods utilizing the knowledge based concept. The target response of the source difference method is the difference between the fine and coarse models (existing approximate model) responses. The coarse model imposes general knowledge behavior of the fine model, thus extrapolation performance and generalization capability of the difference method increase while the number of training data set decreases. In Fig. 2, training phase and final model of SD method are denoted as the dotted line and the bold box, respectively. The training process of ANN during SD modeling can be defined as

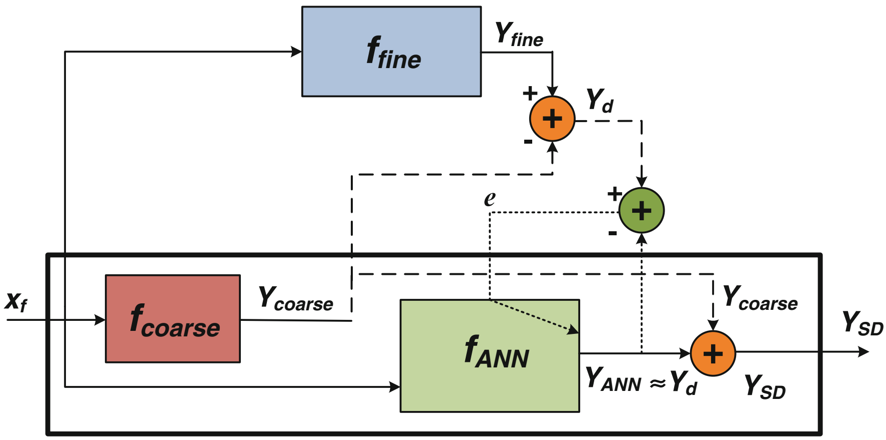

Fig. 2 The training process (updating weight coefficients in terms of error values) and the final model of SD technique embedded the coarse model as the difference between fine and coarse outputs

$$w^* = \arg\min_w \left\| \cdots e^{(i)T} \cdots \right\| \qquad i = 1, 2, \ldots, N. \tag{4}$$

The error term in (4) can be defined as

$$e^{(i)} = \left(\underbrace{f_{fine}\left(x_f^{(i)}\right) - Y_{coarse}^{(i)}}_{Y_d} \right) - f_{ANN}\left(x_f^{(i)}\right) \tag{5}$$

where Y_{coarse} indicates the coarse model response and Y_d indicates the difference between the fine model and the coarse model responses. After the training process of the SD model, the final response of the SD model can be given by

$$Y_{SD} = f_{ANN}\left(x_f\right) + Y_{coarse}. \tag{6}$$

The complexity of ANN can be reduced by the coarse model due to Y_d. Therefore the SD model which is trained by less training data can provide similar accuracy obtained by the ANN model.

3.2 Prior Knowledge Input Method

One of the knowledge based techniques is PKI which requires coarse model response as an extra input besides other inputs that belong to the modeling problem [19, 22]. Since extra inputs which contain extra knowledge other than model inputs enables complexity reduction for the modeling problem. ANN can be formed easily to generate a more accurate response. The training process of ANN during PKI modeling can be defined as

$$w^* = \arg\min_w \left\| \cdots e^{(i)T} \cdots \right\| \qquad i = 1, 2, \ldots, N. \tag{7}$$

The error term in (7) can be defined as

$$e^{(i)} = f_{fine}\left(x_f^{(i)}\right) - f_{ANN}\left(x_f^{(i)}, Y_{coarse}^{(i)}\right). \tag{8}$$

After the training process of the PKI model, the final response of the PKI model Y_{PKI} can be given by

$$Y_{PKI} = f_{ANN}\left(x_f, Y_{coarse}\right) \tag{9}$$

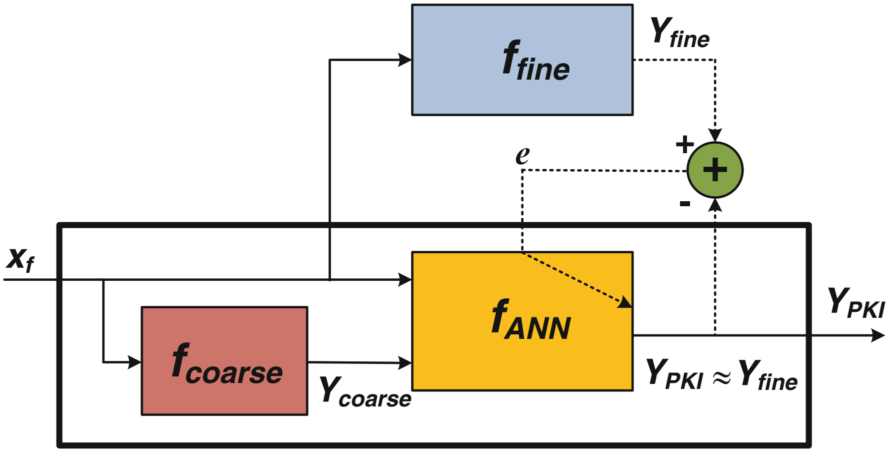

Fig. 3 The training process (updating weight coefficients in terms of error values) and the final model of PKI technique embedded the coarse model as an extra inputs

where Y_{coarse} is used for extra input to the ANN model, hence the accuracy of the PKI model can increase higher than conventional ANN modeling. The training phase and the final model of the PKI are denoted as the dotted line and the bold box in Fig. 3, respectively.

3.3 Prior Knowledge Input with Difference Method

PKI-D as shown in Fig. 4 is developed [13, 14, 19] to exploit the advantage of utilizing the coarse model twice. PKI-D combines extra input property of PKI and learning the output difference Y_d calculated as the difference of fine Y_{fine} and coarse Y_{coarse} models in difference method [19]. ANN forms nonlinear mapping from extended input space with coarse model response to difference between fine and coarse model responses. During the training process, weight coefficients are updated by

$$w^* = \arg\min_w \left\| \cdots e^{(i)T} \cdots \right\| \qquad i = 1, 2, \ldots, N \tag{10}$$

considering the error term defined as

$$e^{(i)} = \left(\underbrace{f_f\left(x_f^{(i)}\right) - Y_{coarse}^{(i)}}_{Y_d} \right) - f_{ANN}\left(x_f^{(i)}, Y_{coarse}^{(i)}\right). \tag{11}$$

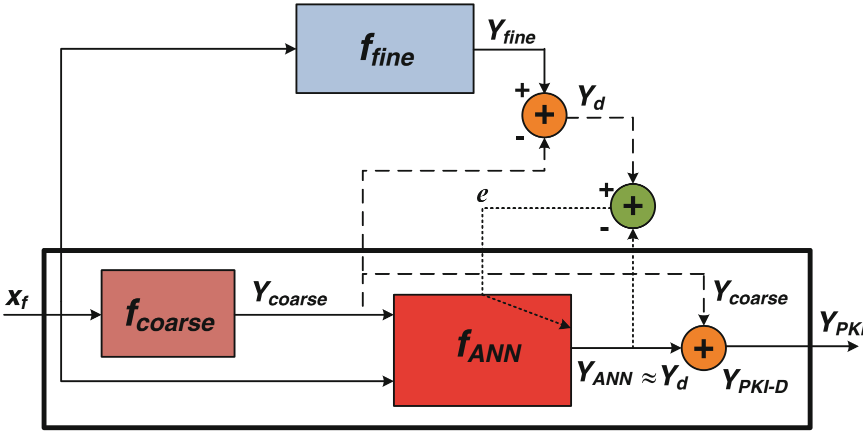

Fig. 4 The training process (updating weight coefficients in terms of error values) and the final model of PKI-D technique embedded the coarse model two times as the extra input and as the difference between fine and coarse outputs

After training is completed, the final model response is ready for the test purpose as follows

$$Y_{PKI-D} = f_{ANN}\left(x_f, Y_{coarse}\right) + Y_{coarse} \tag{12}$$

where Y_{coarse} is used for extra input to the ANN model and also used for obtaining the difference Y_d, hence the accuracy of the PKI-D model can increase higher than conventional ANN modeling due to using this knowledge twice and PKI-D generally provides better accuracy than even other KBANN methods. The training phase and the final model of PKI-D are denoted as the dotted line and the bold box in Fig. 4, respectively.

4 Reconfigurable 5-Fingers Shaped Microstrip Patch Antenna

The Reconfigurable 5-Fingers Shaped Microstrip Patch Antenna (R5FSMPA) [2] is used to perform efficiency of the knowledge based modeling through its three configurations such as ON–ON, ON–OFF, and OFF–OFF states. Since ON–OFF and OFF–ON generate same result, only ON–OFF state is considered. Design parameters of R5FSMPA which are indicated in Fig. 5 are L_1, L_2, and L_3 which represent the length of the radiating patches and W_1, W_2 which represent the width of the radiating patches and W_3 which represents the unfilled space that includes the two PIN diodes (D_1 and D_2) [1]. The feeding coaxial conductor is centered in the middle of L_3 with a radius of 0.065 cm. Two different resistors (R_{D1} and R_{D2}) are

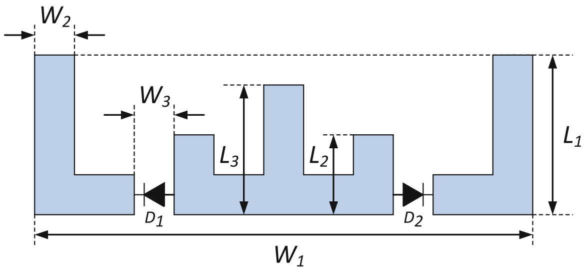

Fig. 5 Physical parameters of R5FSMPA

Table 1 Parameters of reconfigurable 5-fingers shaped microstrip patch antenna (r5fsmpa) and data sets in terms of number of samples

Type of parameters	Input parameters	Training data set		Number of samples		
		Minimum	Maximum	Set-1	Set-2	Set-3
Physical geometry	L_1 (cm)	1.2825	1.4175	3	4	5
	L_2 (cm)	0.7125	0.7875	3	4	5
	L_3 (cm)	0.9975	1.1025	3	4	5
Diode states (ON or OFF)	R_{D1}	5 (ON)	1000 (OFF)	3	3	3
	R_{D2}	5 (ON)	1000 (OFF)			
Frequency sweep	f	1 GHz	7 GHz	200	200	200

utilized with 1000 ohm and 5 ohm values for ON and OFF states of the PIN diodes [8]. Right and left patches of R5FSMPA can be activated through ON and OFF states hence three different combinations can be obtained by two diodes. This section is divided into three parts in terms of the training data set. Each training set has three geometrical parameters, two resistors of diode (ON and OFF states)and frequency as input parameters. Return loss S_{11} as output response is obtained by CST 3D-EM simulations. Physical dimensions of R5FSMPA are given in Table 1.

Input–output relationships of R5FSMPA are shown in Fig. 6 and S_{11} (return loss) is obtained by 3D-EM simulation of CST in terms of 200 number of frequency points between 1 GHz and 7 GHz. The relationship between frequency and S_{11} is indicated by Fig. 7. Three different states of R5FSMPA are modeled via one ANN structure while three states were modeled by three ANN structures in the previous study [2].

In order to demonstrate the efficiency of knowledge based methods, three different data sets can be considered. Selection of data sets is summarized in Table 2 including three data sets. Each data set is utilized as training samples for two different number of neurons in ANN hidden layers. Therefore, all methods can be analyzed in terms of the fundamental ANN properties such as the number of data and the number of neurons to reveal the correlation between accuracy and other ANN parameters.

ANN structure for the conventional ANN is realized by feed-forward multi-layer perceptron (MLP) function in MATLAB Toolbox which utilizes Levenberg-Marquard algorithm and such optimization parameters are: two hidden layer

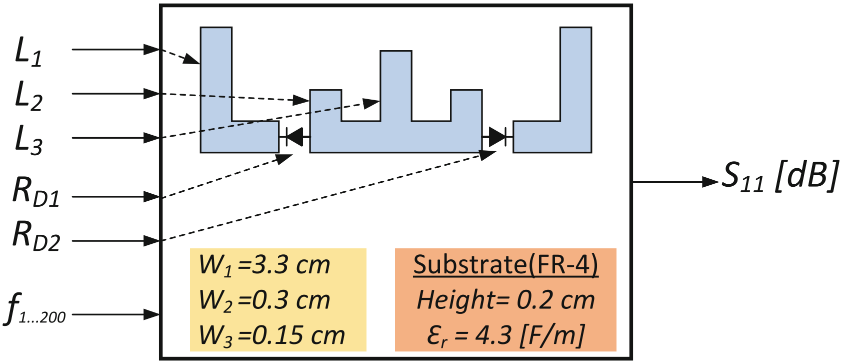

Fig. 6 Input–output relationship of the fine model for R5FSMPA

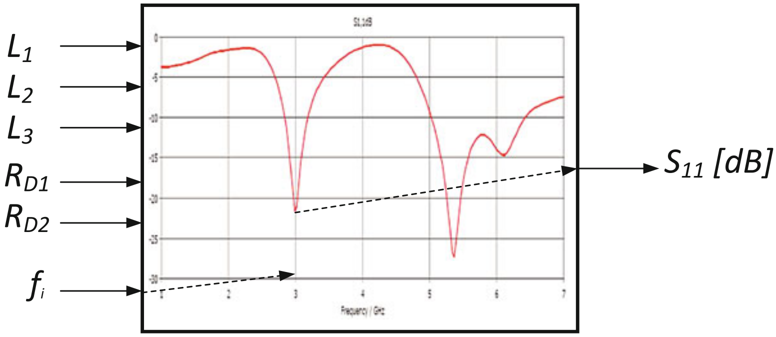

Fig. 7 Frequency-S_{11} relationship of the fine model for R5FSMPA

Table 2 Number of samples for three training data sets and test data

Data type		Geometry L_1 L_2 L_3	Antenna switching states	Frequency 1–7 [GHz]	Total samples
Training	Set-1	3*3*3 = 27	3	200	3*3*3*3*200 = 16,200
	Set-2	4*4*4 = 64	3	200	4*4*4*3*200 = 38,400
	Set-3	5*5*5 = 125	3	200	5*5*5*3*200 = 75,000
Test		3	3	200	3*3*200 = 1800

with different number of neurons, learning rate = 0.1, momentum = 0.2, and regularization = 0.2. Two hidden layer is so suitable for highly nonlinear engineering problem hence it is preferred to form required ANN structure for the knowledge based ANN and conventional ANN methods.

Error calculation is an important part of the comparison. Normalized test error can be formulated by

$$Normalized\ Error = \frac{|Y_{Fine} - Y_{Model}|}{Y_{Fine}} \tag{13}$$

where Y_{Fine} and Y_{Model} indicate the fine model response and the model response which is compared with the fine model response. Normalized mean error can be formulated by

$$Normalized\ Mean\ Error = \frac{1}{N} \times \sum_{i=1}^{N} \frac{|Y_{Fine,i} - Y_{Model,i}|}{Y_{Fine,i}} \tag{14}$$

where i indicates the number of test samples. Normalized max error can be formulated by

$$Normalized\ Max\ Error = \max_{i} \left\{ \frac{|Y_{Fine,i} - Y_{Model,i}|}{Y_{Fine,i}} \right\}. \tag{15}$$

After 20 runs are completed, normalized mean value of S_{11} is calculated for each test sample. Normalized mean and maximum errors are calculated using (14) and (15) in terms of S_{11} obtained from 20 runs.

4.1 *Data Set* – 1*:* 16,200 *Samples*

In this part, three states of the reconfigurable patch antenna are considered in terms of the accuracy and time consumption for data $set - 1$ which consists of three parameters, three states (ON–ON, ON–OFF, and OFF–OFF) and 200 frequency points. The total number of data samples is $16,200$ obtained by three samples selected from the training data interval for three physical geometries which are multiplied by three states and 200 frequencies. Test data which includes nine different geometry is selected from the training interval but each test geometry is different than the training geometry. The test samples consist of three different geometries for three states. Test performance can be demonstrated by one geometry for each states of reconfigurable antenna. Conventional ANN and knowledge based ANN methods run 20 times and average responses of test samples for EM, ANN, and PKI-D are given in Fig. 8 for three different geometries. In addition, normalized test errors of PKI-D and the conventional ANN are given in Fig. 9 for three different geometries.

Accuracy of all methods are summarized in Table 3 for two different ANN structure such as (30–30) and (30–20). Time consumptions of generating data set and the training phase for all methods are given in Table 4 for ANN structure with (30–20) neurons. Since the fine model is computationally complex, it requires more computational time than the coarse model. The coarse model improves the accuracy of all knowledge based methods compared to conventional ANN. The coarse model is used for twice during training of PKI-D, which reduces the complexity of modeling problem. Therefore, time consumption of PKI-D can be less than other knowledge based methods such as SD and PKI.

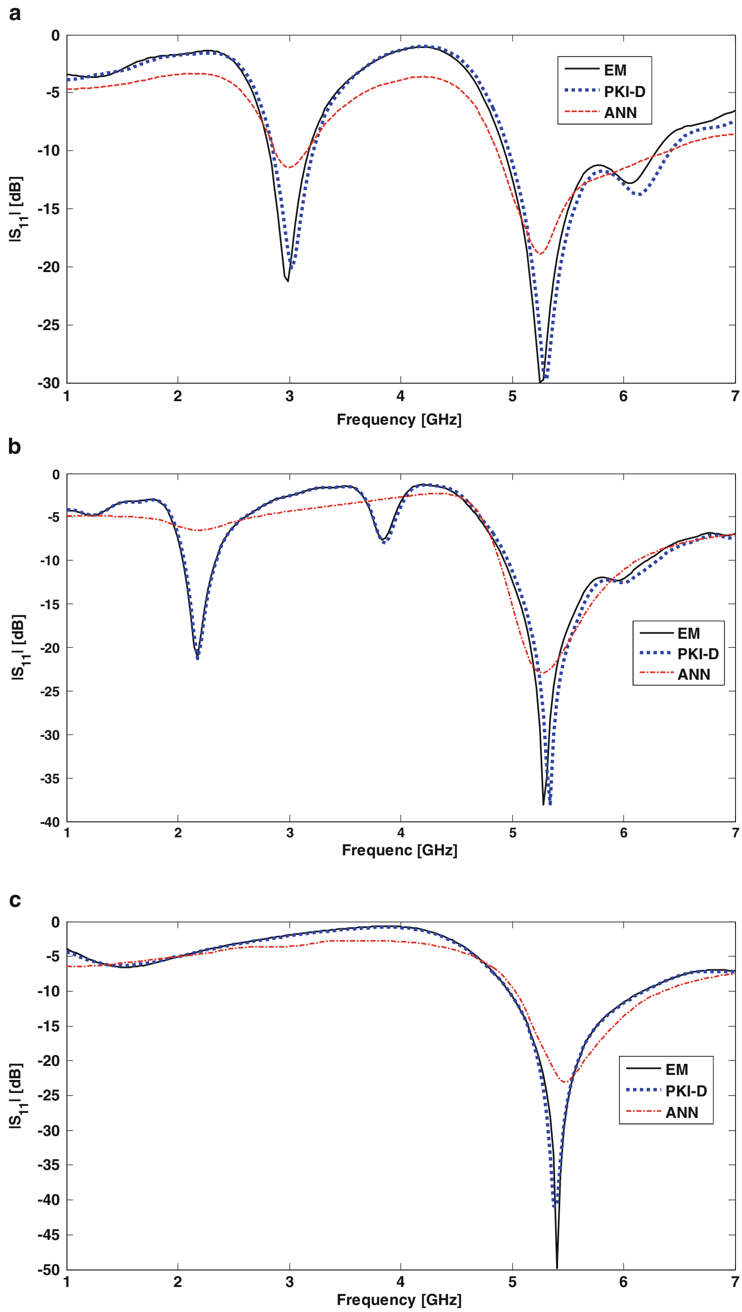

Fig. 8 MLP with two hidden layers (30–30 neurons) trained by 16,200 samples to show EM, PKI-D, and conventional ANN results. (**a**) Magnitude of S_{11} for *Geometry* − 3 (ON–ON case) (**b**) Magnitude of S_{11} for *Geometry* − 6 (ON–OFF case) (**c**) Magnitude of S_{11} for *Geometry* − 9 (OFF–OFF case)

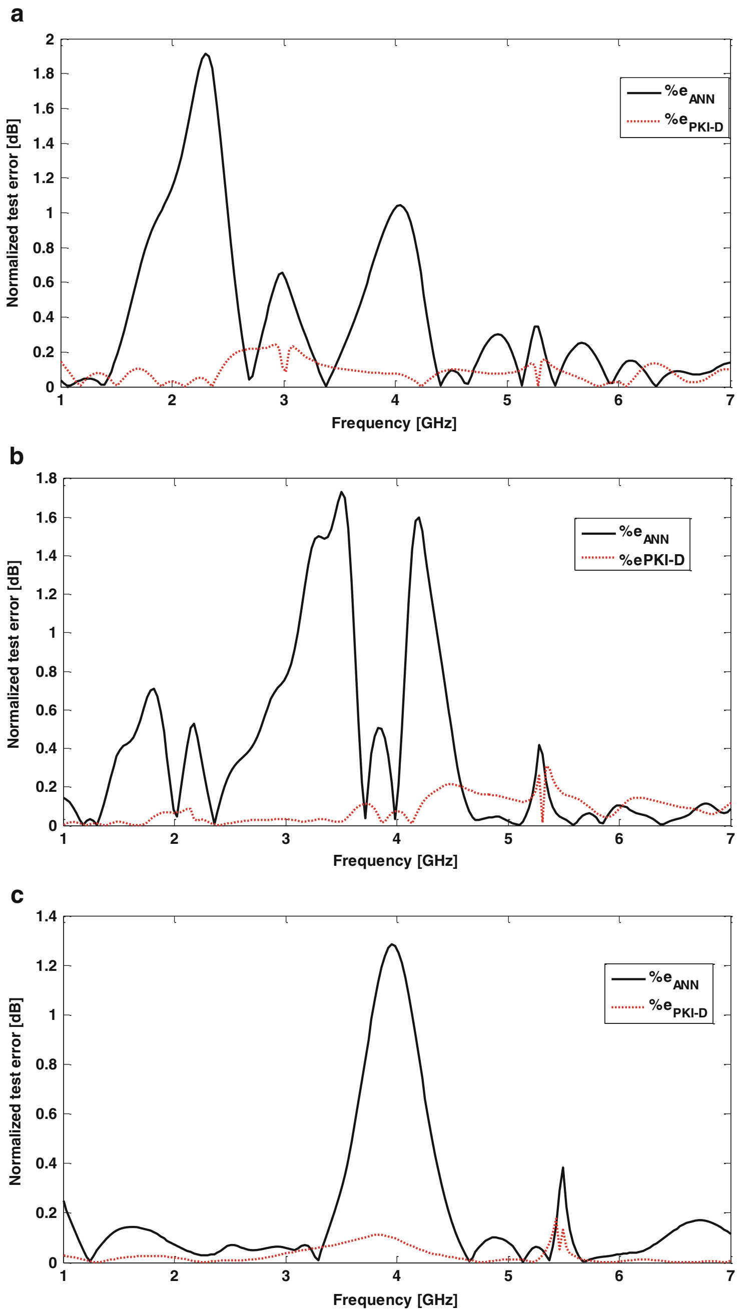

Fig. 9 MLP with two hidden layers (30–30 neurons) trained by 16,200 samples to show EM, PKI-D, and conventional ANN results. (**a**) Normalized test error for *Geometry* − 3 (ON–ON case) (**b**) Normalized test error for *Geometry* − 6 (ON–OFF case) (**c**) Normalized test error for *Geometry* − 9 (OFF–OFF case)

Table 3 Normalized mean errors at 16,200 data samples for all switching states

Tow hidden layers	Error	Coarse (Training)	Coarse (Test)	ANN	SD	PKI	PKI-D
30–30	Mean	0.0485	0.0479	0.3739	0.0628	0.0748	0.0453
	Max	0.4954	0.4719	3.1766	0.4647	1.1451	0.3056
30–20	Mean	0.0485	0.0479	0.3086	0.0630	0.0514	0.0433
	Max	0.4954	0.4719	1.7161	0.4683	0.3423	0.3008

Table 4 Time consumption results of all methods trained by 16,200 data samples for all switching states

	ANN	SD	PKI	PKI-D
Fine	1 h, 11 m	1 h, 11 m	1 h, 11 m	1 h, 11 m
Coarse	–	0 h, 47 m	0 h, 47 m	0 h, 47 m
Max Training	0.462 m	0.217 m	0.220 m	0.203 m
Total	1 h, 11.462 m	1 h, 58.217 m	1 h, 58.220 m	1 h, 58.203 m

4.2 Data Set $-$ **2***:* **38, 400** *Samples*

In this part, three states of the reconfigurable patch antenna are considered in terms of the accuracy and time consumption for data $set - 2$ which consists of three parameters, three states (ON–ON, ON–OFF, and OFF–OFF) and 200 frequency points. The total number of data samples is $34,800$ obtained by four samples selected from the training data interval for three physical geometries which are multiplied by 3 states and 200 frequencies. The same test samples are used for comparing $set - 1$ with $set - 2$. PKI is utilized instead of PKI-D to demonstrate the general performance of knowledge based methods. Conventional ANN and knowledge based ANN methods run 20 times and average responses of test samples for EM, ANN, and PKI are given in Fig. 10 for three different geometries. In addition, normalized test errors of PKI and conventional ANN are given in Fig. 11 for three different geometries.

Accuracy of all methods are summarized in Table 5 for two different ANN structure such as (30–30) and (40–30). Time consumptions of generating data set and the training phase for all methods are given in Table 6 for ANN structure with (40–30) neurons. Since extra knowledge obtained by the coarse model reduces the complexity of modeling problem, knowledge based methods require less time for the training process of ANN structure. Time efficiency in training process of knowledge based methods can be realized in Table 6.

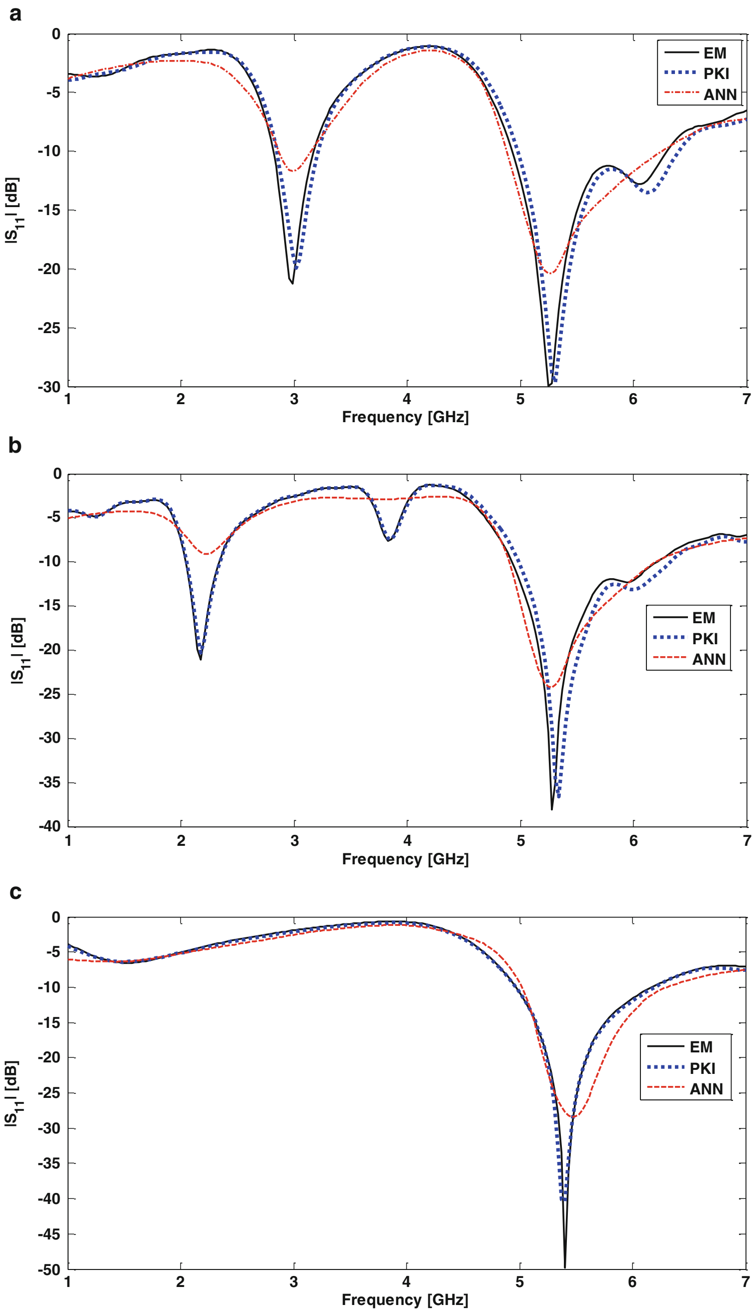

Fig. 10 MLP with two hidden layers (40–30 neurons) trained by 38,400 samples to show EM, PKI, and conventional ANN results. (**a**) Magnitude of S_{11} for *Geometry* − 3 (ON–ON case) (**b**) Magnitude of S_{11} for *Geometry* − 6 (ON–OFF case) (**c**) Magnitude of S_{11} for *Geometry* − 9 (OFF–OFF case)

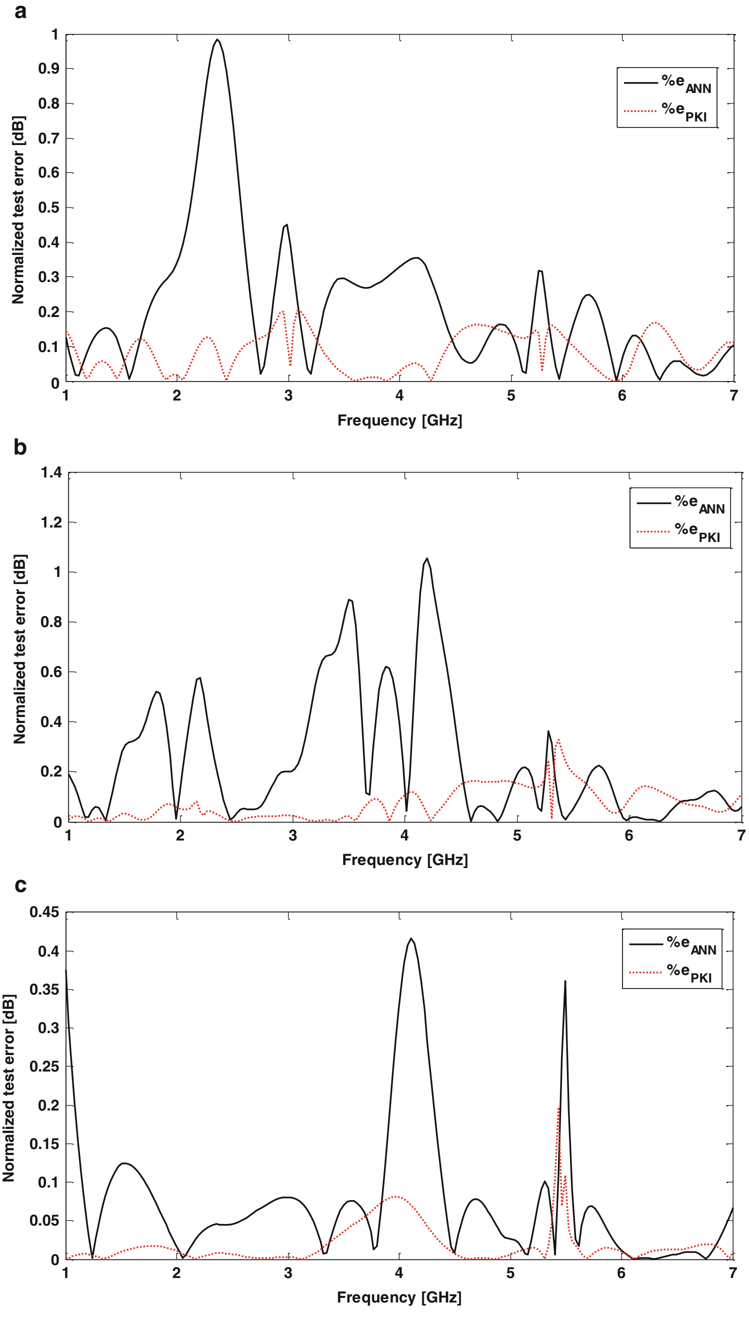

Fig. 11 MLP with two hidden layers (40–30 neurons) trained by 38,400 samples to show EM, PKI, and conventional ANN results. (**a**) Normalized test error for *Geometry* − 3 (ON–ON case) (**b**) Normalized test error for *Geometry* − 6 (ON–OFF case) (**c**) Normalized test error for *Geometry* − 9 (OFF–OFF case)

Table 5 Normalized mean errors at 38,400 data samples for all switching states

Tow hidden layers	Error	Coarse (Training)	Coarse (Test)	ANN	SD	PKI	PKI-D
30–30	Mean	0.0480	0.0479	0.2338	0.0606	0.0475	0.0409
	Max	0.5288	0.4719	1.3846	0.4685	0.3787	0.2645
40–30	Mean	0.0480	0.0479	0.2126	0.0635	0.0428	0.0403
	Max	0.5288	0.4719	1.4164	0.4676	0.3269	0.2747

Table 6 Time consumption results of all methods trained by 38,400 data samples for all switching states

	ANN	SD	PKI	PKI-D
Fine	2 h, 44 m	2 h, 44 m	2 h, 44 m	2 h, 44 m
Coarse	–	2 h, 34 m	2 h, 34 m	2 h, 34 m
Max training	2.679 m	1.028 m	1.116 m	1.016 m
Total	2 h, 46.679 m	5 h, 19.028 m	5 h, 19.116 m	5 h, 19.016 m

4.3 Data Set – 3*: 75, 000 Samples*

In this part, three states of the reconfigurable patch antenna are considered in terms of the accuracy and time consumption for data $set-3$ which consists of three parameters, three states (ON–ON, ON–OFF, and OFF–OFF) and 200 frequency points. The total number of data samples is 75, 000 obtained by five samples selected from training data interval for three physical geometries which are multiplied by 3 states and 200 frequencies. The same test data is used for comparing $set-1$ and $set-2$ with $set-3$. SD is utilized instead of PKI to demonstrate the general performance of knowledge based methods. Conventional ANN and knowledge based ANN methods run 20 times and average responses of test samples for EM, ANN, and SD are given in Fig. 12 for three different geometries. In addition, normalized test errors of SD and conventional ANN are given in Fig. 13 for three different geometries.

Accuracy of all methods are summarized in Table 7 for two different ANN structure such as (45–45) and (50–40). Time consumptions of generating data set and the training phase for all methods are given in Table 8 for ANN structure with (50–40) neurons. Time efficiency in training process of knowledge based methods can be realized in Table 8.

Knowledge based methods generally improve the accuracy of ANN model using even less training data. This improvement is based on extra knowledge about input–output relationship of the modeling problem. This extra knowledge enables to reduce the complexity of the problem. Thus, more accurate results can be obtained by knowledge based methods which utilize less data and fast modeling process. Knowledge based methods provide more accurate results for 16, 200 samples compared to 38, 400 samples for conventional ANN. The performance of knowledge based methods with less training data can be realized in Table 9. Knowledge based

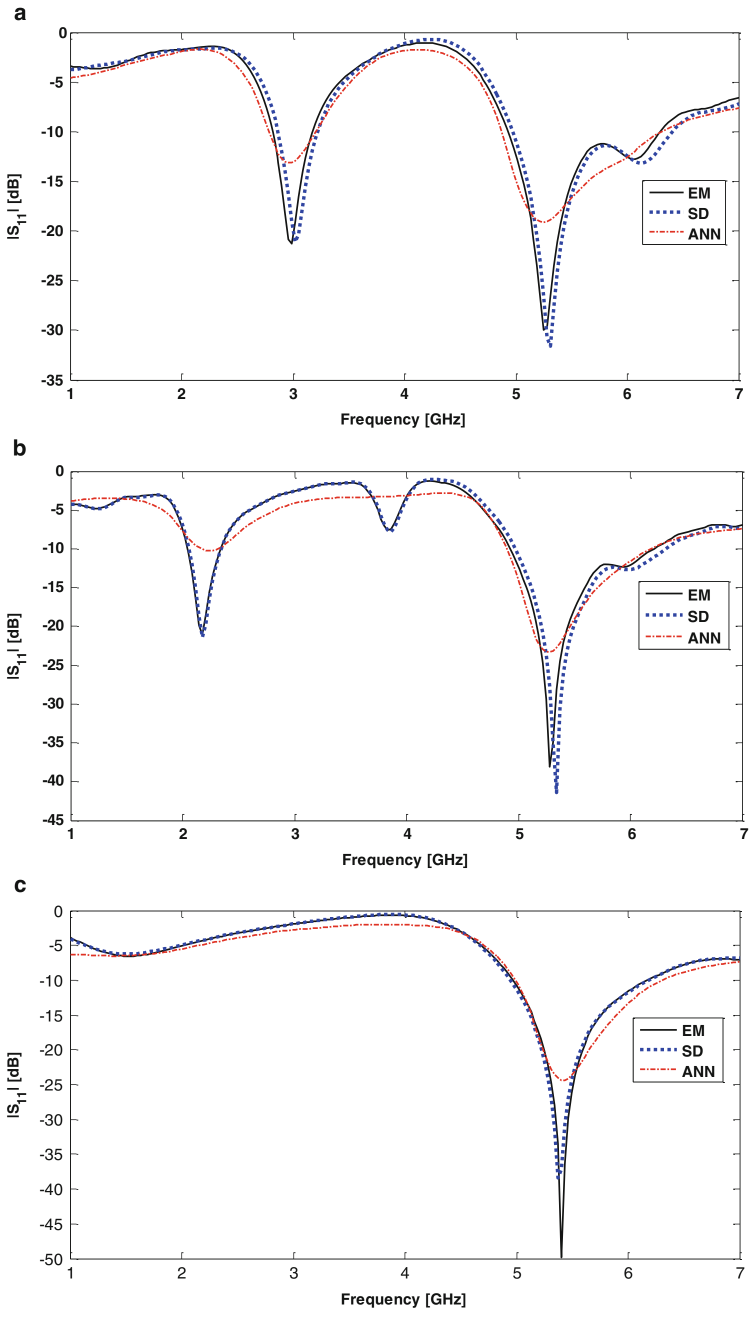

Fig. 12 MLP with two hidden layers (50–40 neurons) trained by 75,000 samples to show EM, SD, and conventional ANN results. (**a**) Magnitude of S_{11} for *Geometry* − 3 (ON–ON case) (**b**) Magnitude of S_{11} for *Geometry* − 6 (ON–OFF case) (**c**) Magnitude of S_{11} for *Geometry* − 9 (OFF–OFF case)

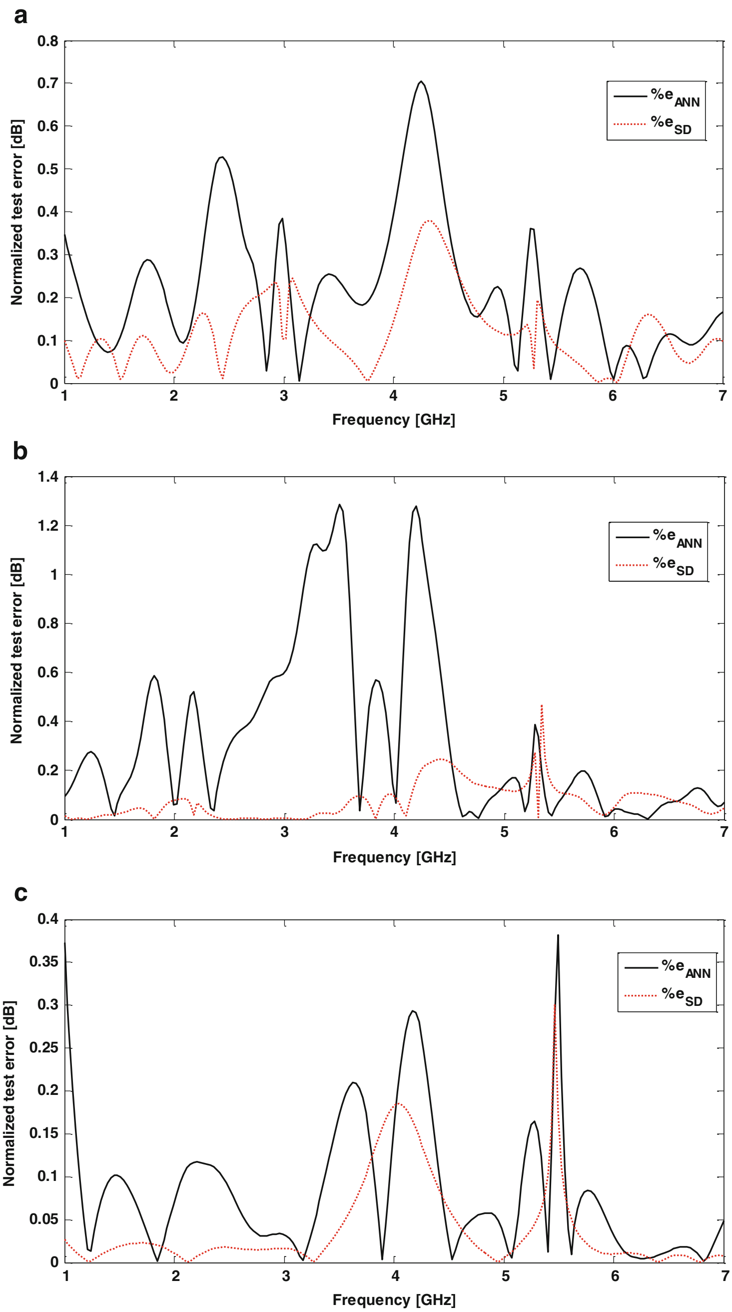

Fig. 13 MLP with two hidden layers (50–40 neurons) trained by 75,000 samples to show EM, SD, and conventional ANN results. (**a**) Normalized test error for *Geometry* − 3 (ON–ON case) (**b**) Normalized test error for *Geometry* − 6 (ON–OFF case) (**c**) Normalized test error for *Geometry* − 9 (OFF–OFF case)

Table 7 Normalized mean errors at 75,000 data samples for all switching states

Tow hidden layers	Error	Coarse (Training)	Coarse (Test)	ANN	SD	PKI	PKI-D
45–45	Mean	0.0475	0.0479	0.1903	0.0592	0.0409	0.0382
	Max	0.6593	0.4719	1.4485	0.4690	0.3682	0.3271
50–40	Mean	0.0475	0.0479	0.2076	0.0583	0.0478	0.0397
	Max	0.6593	0.4719	2.0250	0.4684	0.3265	0.3180

Table 8 Time consumption results of all methods trained by 75,000 data samples for all switching states

	ANN	SD	PKI	PKI-D
Fine	4 h, 22 m	4 h, 22 m	4 h, 22 m	4 h, 22 m
Coarse	–	3 h, 49 m	3 h, 49 m	3 h, 49 m
Max training	3.718 m	1.620 m	1.508 m	2.229 m
Total	4 h, 25.718 m	8 h, 12.620 m	8 h, 12.508 m	8 h, 13.229 m

Table 9 The accuracy comparison of all methods with different data samples and time consumption results for all switching states

Methods	Data samples	Tow hidden layers	Mean error	Max error	Time consumption
SD	16,200	30–30	0.0628	0.4647	1 h, 58.217 m
PKI			0.0748	1.1451	1 h, 58.220 m
PKI-D			0.0453	0.3056	1 h, 58.203 m
ANN	38,400	30–30	0.2338	1.3846	2 h, 46.679 m
ANN	75,000	50–40	0.2076	2.0250	4 h, 25.718 m

methods provide more accurate result for less training data, hence they are so suitable to embed existing knowledge into modeling step of the engineering design process.

5 Conclusion

Knowledge based modeling is applied to engineering modeling relevant to reconfigurable 5-fingers shaped microstrip patch antenna. The aim of this modeling problem is to obtain S_{11} of antenna design parameters corresponding to the frequency. Number of data and number of neurons directly effect ANN performance hence both of them are utilized for the analysis and comparison between knowledge based models and the conventional ANN model. Knowledge based methods with less data are used in order to obtain more accurate results compared to conventional ANN with more data. In addition, knowledge based methods require less time consumption and even less training data through the coarse model efficiency. Knowledge based methods should be selected for the engineering design problem to embed the existing knowledge into the design process. Reconfigurable 5-fingers shaped microstrip patch antenna is selected to demonstrate the efficiency of knowledge based methods which are easily applied to the modeling problem in the engineering design process.

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