A Robust Correction Model Based Neural Network Modeling Framework for Electromagnetic Simulations and RF Measurements

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Abstract — This paper introduces a new artificial neural networks (ANNs)-based correction-modeling approach for simulations and measurements. The proposed approach improves the accuracy of conventional neural models by reversing input-output variables in a systematic manner, while keeping the model structures simple relative to complex knowledge-based ANNs (KBNNs). The approach facilitates accurate/fast neural network modeling of practical electromagnetic (EM) structures, for which, training data is expensive. Two examples are presented to demonstrate the accuracy, efficiency, and feasibility of the proposed modeling approach. The first example is a broadband wire monopole antenna loaded by an annular dielectric ring resonator (DRR) at the antenna feed point. The second example is a metallic waveguide (WG) tube coated with inhomogeneous lossy materials for enhanced electromagnetic interference (EMI) shielding. The proposed approach is significant to RF circuit designers since it helps in building accurate models using reduced numbers of full-wave EM simulations and/or RF measurements.

Index Terms — Artificial neural networks (ANNs), correction based neural network (CBNN), dielectric ring resonator (DRR), waveguide.

I. Introduction

Artificial neural networks (ANNs) have emerged as intelligent and powerful tools to solve nonlinear computing problems. The basic ANN is a 3 layer perceptron known as Multi-Layer Perceptron (MLP3) [1-3]. Here, the accuracy of the neural networks depends on the availability of the training data. ANNs are also considered as black box models and have poor extrapolation and generalization capabilities. To enhance the generalization and extrapolation capabilities Knowledge Based Neural Network (KBNN) were introduced [4]. The most widely implemented KBNNs are Prior Knowledge Input (PKI), Source Difference Method (SDM) and Space Mapped Neural Networks (SMNN). These KBNN method though improve the prediction accuracy compared to ANNs, they lead to increased structural complexity. To improve generalization capability and to reduce structural complexity of existing ANNs, we advocate a new correction-based ANN (CBNN) modeling approach [5]. In the CBNN approach, the less accurate ANN model is supplemented by our "correction model" toward improving the accuracy of the original ANN model. A correction model is obtained by reversing a specific input and output. For a given training data, the number of correction models equals the number of inputs. From among all possible correction models, the one having minimum error is selected. An important step in this approach is to develop a

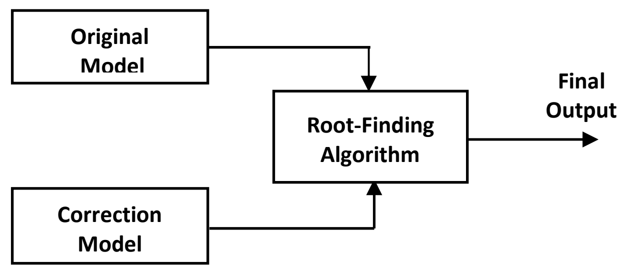


Fig. 1. Correction-based ANN model.

set of possible correction models and to select the best suitable model from within the set. Implementation of the correction and original model pair requires root-finding algorithm as depicted in Fig. 1. Here, we demonstrate the use of a root-finding algorithm, i.e. a "sensitivity-based approach" [6], with combined advantages of Newton's method and steepest-descent method.

Typically, in order to accurately mimic a given device's nonlinear behavior, it is a practice to develop circuit models based on measurement data [7, 8]. However, even if research infrastructure supports adequate measurements, the process of collecting measurement data proves to be exceedingly expensive. Recent advances in full-wave electromagnetic solvers such as 3D EM simulators help validate new modeling approaches using simulation data (avoiding measurements) and, as a result, support advanced research at low R&D cost. Once measurements become available, these new validated approaches can be directly applied for developing measurement data based models.

In this work, we tested our proposed approach by adding uniformly distributed random gross/large errors to a practical EM example as will be demonstrated in the following section.

This paper is organized as follows: Section II describes the proposed Correction Based Neural Network (CBNN) approach, Section III depicts the implementation of proposed method to two examples: a dielectric ring resonator antenna and a waveguide metallic tube coated with lossy materials. Section IV summaries the work.

II. Proposed Correction Based Neural Network (CBNN)

The proposed CBNN [5] approach includes the conventional neural model f_{ann} and a set of correction models $f_{ann,j}$ in order to achieve the condition $E_{obj} < E_{user}$ and improve the prediction accuracy of f_{ann}. Here, E_{user} is a user defined error and E_{obj} is the validation error of each sample in $f_{ann,j}$ given as

$$E_{obj} = \frac{original - predicted}{original} X100 \quad (1)$$

The desired output of correction model is taken as j^{th} element of input vector in f_{ann} and the input is replaced with the j^{th} element of f_{ann} desired output.

$$x_{j,c} = f_{ann,j}(y, x_{j+1}, x_{j+2}, \ldots, w_j), \quad (2)$$

Where, $x_{j,c}$ is the desired output of j^{th} correction model. After training and validating all the correction models, the best candidate correction model has to be identified based on the error criterion E_{avg}, given in eq. (3).

$$E_{avg} = \frac{1}{N_v} \sum_{j=1}^{N_v} \left| \frac{f_{ann}(x_j, w) - y_j}{y_{max} - y_{min}} \right| \quad (3)$$

Where, N_v is the number of training samples, y_j is the actual output and $f_{ann}(x_j, w)$ is the predicted output to the input vector x_j.

Based on the error criterion once the best candidate correction model is identified, it is combined with the less accurate f_{ann} using a root finding algorithm. The root finding algorithm is iteratively implemented such that the condition $E_{obj} < E_{user}$ is satisfied. Here, partial derivatives are employed to find the step-size and update direction, this approach is named as a sensitivity-based root finding algorithm [6]. The partial derivatives of the candidate correction model $f_{ann,j}$ with respect to output y is obtained by applying the chain rule of calculus and is given as

$$\frac{\partial x_{j,c}}{\partial y} = \sum_{k=1}^{r} \frac{\partial x_{j,c}}{\partial z_k} \frac{\partial z_k}{\partial y_k} \frac{\partial y_k}{\partial y} \quad (4)$$

In eq. (4), r is the number of hidden neurons, y_k is weighted sum of all inputs to $f_{ann,j}$ and z_k is the sigmoid activation function. The sigmoid activation function is computationally better over other functions such as arc tangent or hyperbolic tangent; hence it is employed in ANN training.

In the initial stages of implementing the root finding algorithm, output y from f_{ann} is taken as the initial input and applied on "f_{ann} and $f_{ann,j}$ pair". The output y is then constantly updated using a root finding algorithm until the condition $E_{obj} < E_{user}$ is satisfied for each subsample in the dataset. The proposed CBNN is implemented on a dielectric ring resonator antenna and a metallic rectangular waveguide tube coated with lossy material as demonstrated below.

A. Dielectric Ring Resonator (DRR) Antenna

Typically, all resonant antennas provide narrow bandwidth due to limited input impedance matching. In order to meet the demand of emerging broadband wireless services, a few techniques have been successfully employed to increase the operational bandwidth, especially on wire monopole antennas, which have narrow bandwidth. External matching networks were utilized to broaden an antenna impedance bandwidth [9, 10]. One way to address this issue is to employ a single cylindrical dielectric resonator over a ground. Increasing the bandwidth of a cylindrical dielectric resonator antenna (DRA) can be achieved by removing a section of the central portion of the dielectric resonator to form a dielectric ring resonator (DRR) antenna as shown in Fig. 2. This provides low effective dielectric constant and low Q-factor of the DRR, and an increase in the antenna impedance bandwidth.

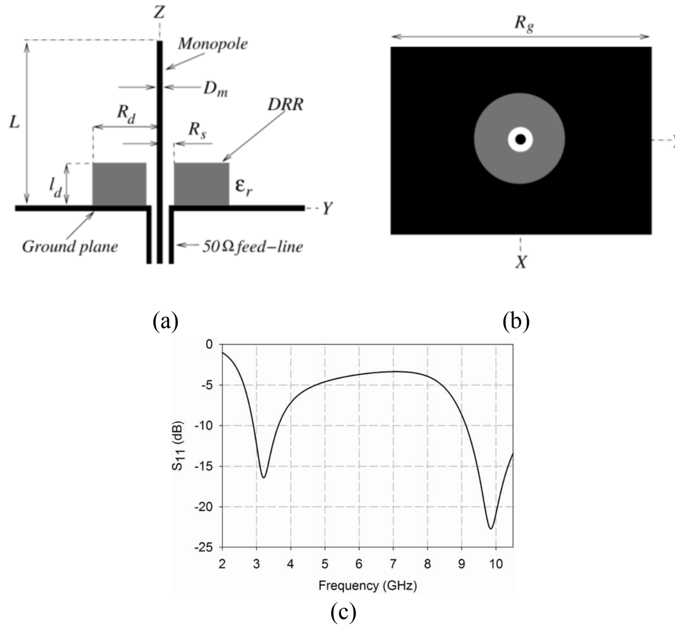


Fig. 2. (a) Cross-sectional view of the broadband monopole-DRR antenna; (b) its top view; and (c) the simulated reflection coefficient (S_{11}) of the monopole wire antenna without the DRR showing narrow impedance bandwidth at 3.2 GHz.

Training data of the wire monopole antenna loaded by a DRR has been prepared. Reflection coefficient (S_{11}) data versus frequency for different values of the annular DRR height and dielectric constant have been established. The training data were then utilized to develop the proposed CBNN model.

B. Metallic Waveguide (WG) Tube

To mitigate intentional and unintentional electromagnetic interference (EMI) sources from penetrating a device or to prevent internal RF emissions from escaping a device, using metallic enclosures of electronic circuits is one of the fundamental remedies [11]. Typically, for high levels of attenuation, the shield must have no penetrations (e.g., seams, holes, and cables). However, this may not be an option for applications where air ventilation is required for thermal reasons. In such cases, metallic waveguide (WG) tubes operating below the cutoff frequency (f_c) are used as EMI shields while providing airflow into the enclosure [12]. In this example of Fig. 3, a rectangular WG with a width (W) of 34 mm, a height (H) of 14 mm, a length (L) of 100 mm, and a coating thickness (t) of 2 mm was chosen and was excited by its dominant TE_{10} mode. The WG with lossless metallic walls has an f_c of 4.41 GHz. Training data of the WG with stepped coating materials along the WG length have been established. Insertion loss (S_{21}) simulation results versus frequency for different segment lengths of the coating materials within the WG given length, permeability of lossy magnetic materials, and permittivity of lossy dielectric materials have been employed as training data and utilized for the development of the proposed CBNN model. The segment length ($L_m = L_d$), permittivity and permeability ($\varepsilon_r = \mu_r$), and frequency (f) are taken as three inputs and S_{21} is taken as the output.

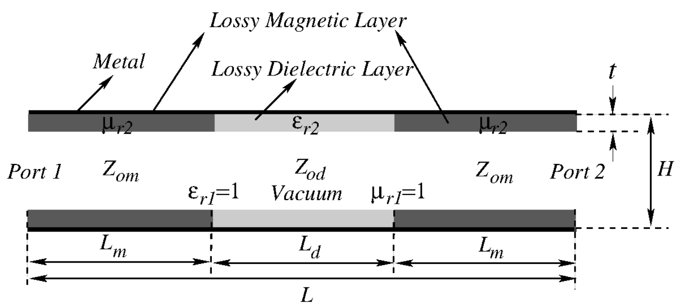


Fig. 3. Side cross-section view of the WG coated with three segments of lossy materials as an example. The stepped variations consist of the following order: lossy magnetic-dielectric-magnetic along the WG length (L).

III. Results and Discussions

The proposed CBNN is trained and validated for 40 hidden neurons using Quasi Newton training algorithm. The basic 3 layer MLP with sigmoid activation function is utilized. The antenna and waveguide examples are implanted using CBNN.

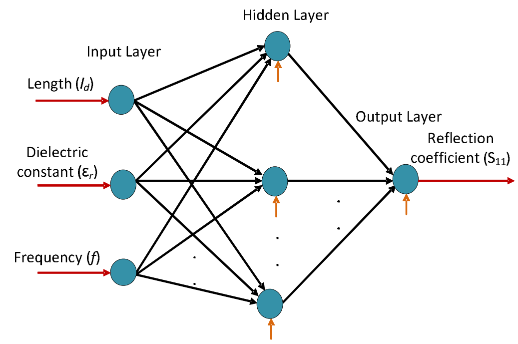
A. Results from the DRR Antenna

The objective of antenna example is to develop a computational model, i.e. ANN model, with annular dielectric ring resonator length, dielectric constant, and frequency as inputs and corresponding reflection coefficient as output. Development of a straightforward ANN model resulted in a high modeling error of 3.42%. Hence, we went ahead and applied the proposed approach. Three correction models are developed, using length (l_d), dielectric constant (ε_r), and frequency (f) as outputs. The prediction errors of all possible correction models are tabulated as follows:

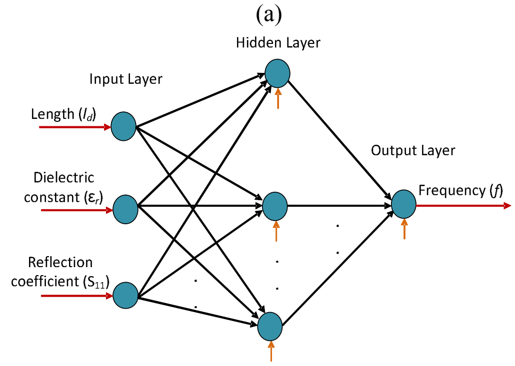
TABLE I
Prediction Error of the Possible Correction Models for the Monopole DRR Antenna Example

Correction Model Output	Prediction Error (%)
Length (l_d)	19.59
Dielectric constant (ε_r)	32.68
Frequency (f)	18.71

The original ANN model and the selected correction model are as shown in Fig. 4(a) and 4(b) respectively. As observed from Table I, the correction model with frequency as output has the least prediction error. Hence, frequency correction model is selected as the best correction model and is used to help the original ANN model using sensitivity-based root-finding algorithm. It is observed that the proposed CBNN model outperformed the traditional stand-alone ANN by significantly reducing the prediction error from 3.42% to 2.17%. Fig. 5 depicts the reflection coefficient S_{11} results using HFSS[1], CBNN, and ANN. As can be observed, the proposed CBNN model matches the HFSS simulations.



(a)



(b)

Fig. 4. (a) ANN model for antenna example; and (b) its selected CBNN model.

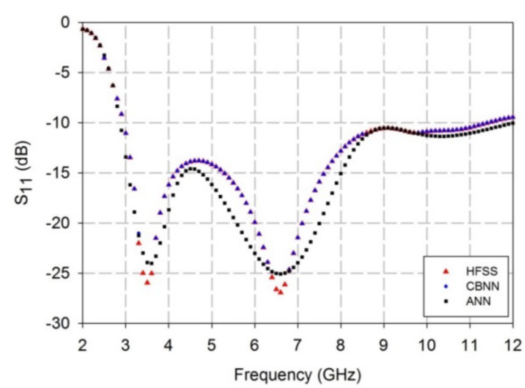


Fig. 5. Reflection coefficient (S_{11}) results of the monopole DRR antenna using HFSS, proposed CBNN, and ANN.

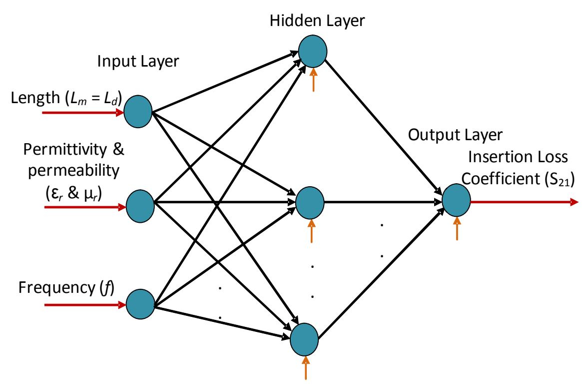
[1] Ansys-HFSS 14, http://www.ansys.com

B. *Results from the Metallic WG Tube*

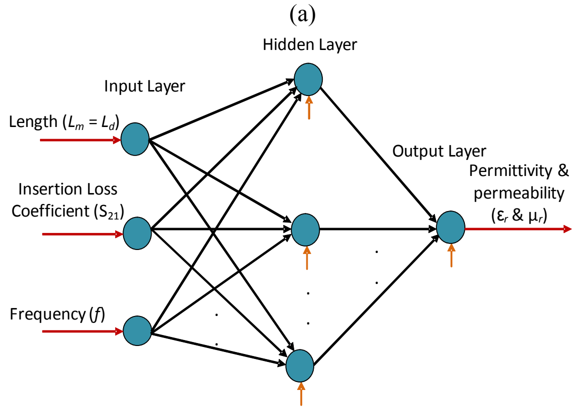
In case of Waveguide example, the straightforward ANN model resulted in an error of 3.06%. Hence, the proposed CBNN has been applied. There are three correction models with segment length, permittivity and permeability, and frequency as output parameters. From Table II, permittivity and permeability correction model has minimum prediction error compared to other correction models. Therefore, permittivity /permeability correction model and original ANN form a mutually supportive pair and are modeled using sensitivity based root-finding algorithm. The ANN model and the selected correction model are shown in Fig. 6.

TABLE II
PREDICTION ERROR OF THE POSSIBLE CORRECTION MODELS FOR THE WAVEGUIDE EXAMPLE

Correction Model Output	Prediction Error (%)
Segment length ($L_m = L_d$)	9.09
Permittivity & permeability (ε_r & μ_r)	4.43
Frequency (f)	10.09



(a)



(b)

Fig. 6. (a) ANN model for antenna example; and (b) its selected CBNN model.

As mentioned earlier, the advent of EM simulators has advanced computer aided modeling research by avoiding RF measurements during the research phase. In practice, hardware limitations in RF measurement instruments (e.g., VNAs) are common. For example, noise floor of an RF instrument can significantly affect S-parameter measurement results. Such results become unusable when the noise floor is sufficiently above the measurement of interest and assuming that noise effects can be avoided with sufficient reduction in IF bandwidth or increase in averaging factor may not be a practical assumption in most scenarios. Building models in the presence of gross errors is essential and automatically removing such errors from measurement data is important.

Our proposed modeling approach is extended to model more realistic data based on EM simulations but with uniformly distributed random gross/large errors emulating RF measurements. The errors were added by taking into account the effect of an RF measurement instrument noise floor on S-parameters below -150 dB (assuming -150 dB dynamic range of the equipment[2]). This slightly modified example with insertion loss values of more than 150 dB (i.e., S_{21} with values <= -150) is a decent candidate to illustrate the robustness of the proposed approach. For this special case, the proposed modeling approach was cascaded into two-stages with the first stage being an automatic gross measurement error removal stage and the second stage being proposed CBNN. In the first stage, we train an MLP network with the erroneous training data using Huber quasi Newton (HQN) algorithm [13]. The HQN smartly avoids teaching the MLP with gross/large errors in the training data. Fig. 7 depicts the percentage error of output samples after training using HQN. By setting an error threshold of 15%, the proposed first stage automatically removes the erroneous data samples (representing gross/large and random measurement errors) from the training data. The error free training data is then modeled using the proposed CBNN. The possible correction models are with segment length, permittivity, and frequency as desired outputs. From Table III, the correction model with segment length as output has minimum prediction error and is chosen as the desired correction model.

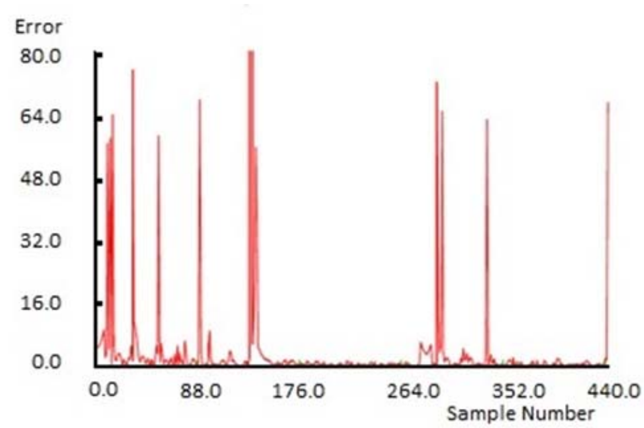


Fig. 7. Graph showing percentage error after training using Huber-Quasi Newton algorithm.

[2] Copper Mountain Technologies, http://www.coppermountaintech.com

TABLE III

PREDICTION ERROR OF THE POSSIBLE CORRECTION MODELS FOR THE WAVEGUIDE EXAMPLE

Correction Model Output	Prediction Error (%)
Segment length	10.67
permittivity	11.42
Frequency	11.07

The accuracy of stand-alone and traditional MLP network is again improved, i.e. modeling error decreased from 3.06% to 2.70%. Fig. 8 represents the insertion loss S_{21} using HFSS, proposed CBNN, and ANN. The proposed CBNN model closely agrees with HFSS simulations.

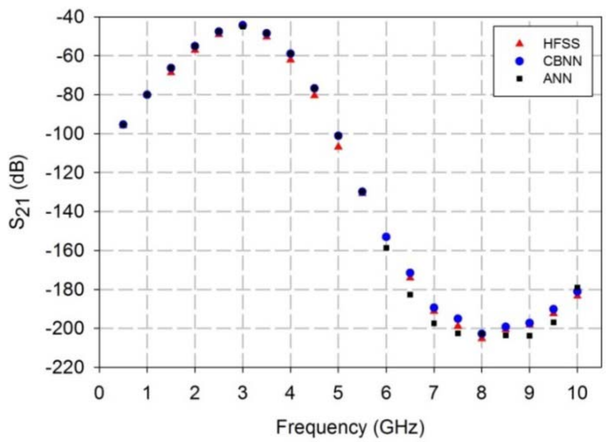


Fig. 8. Insertion loss (S_{21}) results of the WG using HFSS, proposed CBNN, and ANN.

The proposed two-stage modeling approach has improved ANN accuracy by reducing the modeling error from 5.75% (using straightforward MLP network) to 4.74% (using the proposed CBNN). Fig. 9 shows S_{21} using HFSS, proposed CBNN, and ANN, where the proposed CBNN closely agrees with the HFSS simulations.

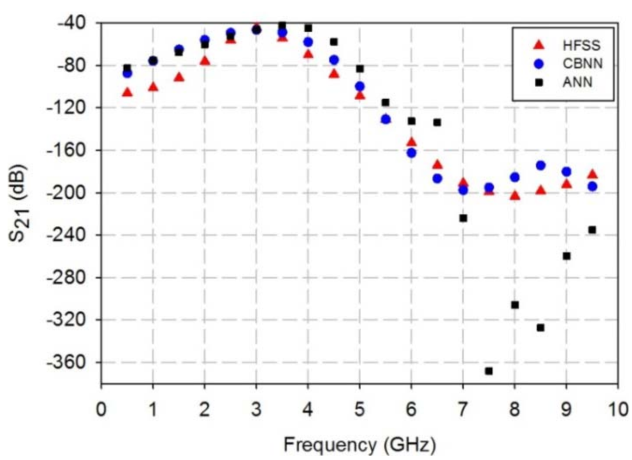


Fig. 9. Simulated S-parameter transmission coefficient (S_{21}) of the waveguide example using HFSS, proposed two-stage CBNN and ANN.

A comparison of proposed CBNN and ANN is presented in Table IV, as follows. It is clearly seen that proposed CBNN outperforms ANN in both the examples discussed and even under the effect of noise.

TABLE IV

PREDICTION ERROR OF THE PROPOSED CBNN AND ANN MODELS FOR ANTENNA AND WAVEGUIDE EXAMPLES

Modeling Approach	PEDICTION ERROR (%)		
	Antenna example (without noise)	Waveguide example (without noise)	Waveguide example (with noise)
ANN	3.422%	3.063%	5.758%
CBNN	2.173%	2.708%	4.743%

IV. CONCLUSION

In this article, a Correction Based Neural Network approach is proposed to model electromagnetic simulations and RF measurements. The proposed model is applied to a broadband wire monopole antenna loaded by an annular dielectric ring resonator (DRR) at the antenna feed point and a metallic waveguide (WG) tube coated with inhomogeneous lossy materials for enhanced electromagnetic interference (EMI) shielding. For both the examples the proposed model outperformed the conventional ANN and matches with the standard HFSS simulations. In terms of future work, exploring various root finding algorithms and testing their applicability to the current application by varying the number of hidden neurons and training algorithms.

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