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Review paper

PRIOR KNOWLEDGE BASED NEURAL MODELING OF MICROSTRIP COUPLED RESONATOR FILTERS

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Abstract. *The design of microstrip coupled resonator filters includes determination of the coupling coefficients between the filter resonator units. In this paper a novel modeling procedure exploiting prior knowledge neural approach is proposed as an efficient alternative to the standard electromagnetic (EM) simulations and to the neural models based purely on the artificial neural networks (ANNs). It has similar accuracy as the EM simulations and requires less training data and less time needed for the model development than the models based purely on ANNs.*

Key words: *artificial neural networks, coupled filters, design, microstrip*

1. INTRODUCTION

Microstrip coupled resonator filters act as bandpass filters and they are widely exploited in the modern microwave communication systems. Planar filters are a good choice for realizing low passband loss and high rejection ratio in the stopband. They are manufactured easily to utilize printed circuit board (PCB) technology with a high accuracy and a relatively low price. Planar filters' responses do not vary when manufactured in series and their adjustment and tuning is straightforward. The variety of classical and cross-coupled topologies of microstrip filters can realize the Chebyshev equiripple and quasi-elliptic response. The preferred resonators for practical realizations are half-wavelength resonators and their compact variants- hairpin and square open loop resonators [1].

The square open loop resonators offer compact size at good quality factor inhering the frequency properties of the half wavelength resonator. As many microwave systems are relatively narrowband, the square open loop resonator can realize the narrow bandwidths with weak coupling coefficients at reasonable distance between them.

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The cross-coupled filters with quasi-elliptic frequency response require clear identification of the sign of the coupling coefficient, which leads to clarification of the electrical, magnetic or mixed type of coupling especially between the non-adjacent resonators. The square open loop resonators solve this difficulty comparing to the half-wavelength resonators with the benefit of flexibility of coupling topologies.

The filter synthesis process follows the classical approach through the calculation of the coupling matrix according to the chosen approximation. In the microwave systems, the most popular and implemented approximation is the Chebyshev one [2]-[3]. In [2] the design process of the polynomials and the transversal coupling matrix is given. Many authors offer matrix rotations to transform the canonical or transversal matrix to the exact matrix corresponding to the chosen topology [1]-[2]. An optimization method for direct calculation of the interresonator coupling coefficients is proposed in [4]. Nevertheless, whatever method for synthesis is chosen, the distance between the resonators should be calculated precisely. In [1] it is proposed to utilize a full-wave EM simulator, which is a rigorous approach, but suffers from a high time consumption and high calculation power needed.

To overcome time consuming EM simulations or complex optimization methods, new approaches based on application of artificial neural networks (ANNs) have been proposed to model the filter coupling properties on the filter resonator physical dimensions and/or the properties of the chosen dielectric material [5]-[6]. Moreover, the ANN based approach has been applied to perform inverse modeling of the filter. Namely, the ANNs are used to determine the distance between the filter resonators for the given coupling properties [7]-[8] or resonator dimensions and the given coupling coefficient [5]-[6]. However, the developed models of the filter coupling properties shown in [5] are valid for only one considered dielectric material (i.e., for one specified value of the relative dielectric constant). In other words, it means that for each dielectric material it is necessary to develop a new neural model. To build a model which would be valid for different values of the relative dielectric constant, it would be necessary to acquire a bigger amount of the EM simulated data, which would be time consuming and thus making the whole modeling procedure inefficient. In this paper we propose a novel approach in microstrip coupled resonator filter modeling, which is based on the prior knowledge based neural approach. Namely, instead of exploiting the ANNs only, here the ANNs are combined with the empirical formulae, aimed for the approximate determination of the filter coupling coefficient. This approach provides a single model for all considered values of the relative dielectric constant. Moreover, the model can be built with less data than the separate purely ANN based models.

The rest of the paper is structured as follows. The considered microstrip coupled resonator structure as well as the empirical expressions used for approximate determination of the filter coupling coefficients are described in Section 2. Section 3 contains a brief background of the prior knowledge neural approach. The novel prior knowledge neural model is proposed in Section 4, whereas the obtained results and the discussion are given is Section 5. Section 6 contains conclusions.

2. Microstrip Coupled Resonator Filters

The square open loop resonator is a half wavelength long microstrip line with open ends (see Fig.1a). The form of the resonator is symmetrical and the electromagnetic field distribution along it is predictable due to the symmetry. The open ends are supposed to be shortened, because of the fringe capacitance [9]-[10].

(a) (b)

Fig. 1 (a) The topology of microstrip square open loop resonator, (b) an example of coupled resonators

The different orientations of the resonators on the top plane of the substrate form various kinds of coupling topologies. The coupling mechanism is achieved by the fringe fields, when the resonators are adjacent each other. The electrical filed is stronger than the magnetic near the open end of the resonator and the magnetic field is predominant at the center of the resonator. The strength of the electrical field and magnetic field decays rapidly with the distance from the open end and the center of the resonator respectively. The coupling structures in Fig.1b perform mixed coupling. It is not possible to determine which field is dominant. The value of the coupling coefficient of the coupled resonators in Fig1.b is much lower, because the currents are out-of-phase. This topology is applicable in narrow bandwidth filters.

The considered microstrip resonator is of a square shape with the length *a* and the line width *w*, fabricated on the substrate having the height *h* and the relative dielectric constant ε_r. The coupling coefficient (including mixed electric and magnetic coupling) k is precisely calculated in the EM simulators, but the rough value of the coupling coefficient can be calculated using the following expressions [11]:

$$k = k_e^{'} + k_m^{'}\,, \tag{1}$$

$$k_m^{'} = 0.5 \cdot k_m\,, \tag{2}$$

$$k_e^{'} = 0.6 \cdot k_m \tag{3}$$

The coefficient of magnetic coupling k_m and the coefficient of electric coupling k_e are calculated as:

$$k_e = \frac{\pi}{16} \cdot F_e \cdot \exp(-A_e) \cdot \exp(-B_e) \cdot \exp(-D_e)\,, \tag{4}$$

$$k_m = \frac{\pi}{16} \cdot F_m \cdot \exp(-A_m) \cdot \exp(-B_m) \cdot \exp(-D_m)\,, \tag{5}$$

where:

$$A_e = 0.2259 - 0.01571 \cdot \varepsilon_r + 0.1\sqrt{\varepsilon_r + 1} \cdot \frac{w}{h}, \tag{6}$$

$$B_e = \left(1.0678 + 0.226 \cdot \ln\left(\frac{\varepsilon_r + 1}{2}\right)\right) \cdot \left(\frac{s}{h}\right)^{pe}, \tag{7}$$

$$p_e = 1.0886 + 0.03146 \cdot \left(\frac{w}{h}\right)^4, \tag{8}$$

$$D_e = \left(0.1608 - 0.06945\sqrt{\frac{a}{h}}\right) \cdot \left(\frac{s}{h}\right)^{1.15}, \tag{9}$$

$$F_e = \left(-0.9605 + 1.4087\sqrt{\frac{a}{h}} - 0.2443 \cdot \frac{a}{h}\right), \tag{10}$$

$$A_m = \left(-0.06864 + 0.14142\frac{w}{h} + 0.08655\left(\frac{w}{h}\right)^3\right), \tag{11}$$

$$B_m = 1.2 \cdot \left(\frac{s}{h}\right)^{pm}, \tag{12}$$

$$p_m = 0.8885 - 0.1751\sqrt{\frac{w}{h}}, \tag{13}$$

$$D_m = \left(1.154 - 0.8242\sqrt{\frac{a}{h}} + 0.1417 \cdot \frac{a}{h}\right) \cdot \left(\frac{s}{h}\right), \tag{14}$$

$$F_m = -0.5014 + 1.0051\sqrt{\frac{a}{h}} - 0.1557 \cdot \frac{a}{h}. \tag{15}$$

3. Prior Knowledge Neural Modeling Approach

Owing to their excellent fitting capabilities artificial neural networks have found many applications in the field of RF and microwaves [12]-[19]. Most of the applications have been based on the black-box modeling approach, which means that one or more ANNs are used to extract the relationship between the sets of the input and the output parameters (see Fig. 2a). However, in order to make the modeling procedure more efficient, less time consuming and more accurate, without increasing the number of training data, the prior knowledge input (PKI) neural approach can be applied (see Fig. 2b) [12]. Namely, in the PKI approach, beside the original *n* input parameters, there are additional inputs of the ANN. They represent the prior knowledge, meaning that they are correlated in some extent with the output parameters. In general, the number of prior knowledge input parameters (*l*) can be equal, but not necessary, to the number of the output parameters (*m*). The prior knowledge can be, for instance, the values of the outputs which are obtained by an approximate or simplified method.

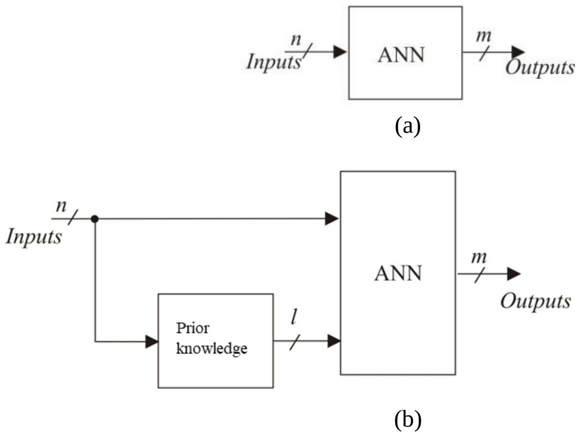


Fig. 2 (a) Black-box neural modeling approach, (b) Prior knowledge input neural modeling approach

The ANNs used in this work are the multilayer perceptron networks, having one input, one output and one or two hidden layers [12]. The transfer function of the input layer neurons is a unitary transfer function. The hidden layer neurons have sigmoid transfer functions, whereas the output layer neurons have linear transfer function. The Levenberg-Marquardt algorithm is used for the ANN training. The PKI approach requires that for each data sample used for the ANN training, as well as later for testing and employing the developed model, it is necessary to have the values of the prior knowledge parameters.

The average test error (ATE), the worst case error (WCE) and the Product-Pearson correlation coefficient (r) have been used as the metrics for comparing the models [11].

If the error of the ANN response for the i–th input combination (i-th sample), k_i compared to the corresponding target value, k_{ti}, relative to the dynamic range of the target values in the test set ($k_{t\,\max} - k_{t\,\min}$) is calculated as

$$\delta_i = \frac{k_i - k_t}{k_{t\,\max} - k_{t\,\min}} \,. \tag{16}$$

The ATE, WCE and r are defined as follows:

$$ATE = \frac{1}{N}\sum_{i=1}^{N} |\,\delta_i\,| , \tag{17}$$

$$WCE = \max_{i=1}^{N} |\,\delta_i\,| , \tag{18}$$

$$r = \frac{\sum_{i=1}^{N} (|\,k_i\,| - |\,\bar{k}\,|)(|\,k_i\,| - |\,\bar{k}\,|)}{\sqrt{\left[\sum_{i=1}^{N} (|\,k_i\,| - |\,\bar{k}\,|)^2\right]\left[\sum_{i=1}^{N} (|\,k_{ti}\,| - |\,\bar{k}_t\,|)^2\right]}} , \tag{19}$$

where N is the number of the samples in the training set, and $\overline{k}$ and $\overline{k_t}$ mean values of the ANN response and the target values, respectively:

$$\overline{k} = \frac{1}{N}\sum_{i=1}^{N} k_i \text{ and } \overline{k_t} = \frac{1}{N}\sum_{i=1}^{N} k_{ti} . \tag{20}$$

4. Proposed Model

In the proposed model, an ANN (Fig. 3) is trained to predict the coupling coefficient for the given resonator dimensions a, s, w, the substrate height h and the relative dielectric constant ε_r. Besides these original input parameters, the ANN has an additional input representing the prior knowledge, which is the approximate value of the coupling coefficient, here marked as k_{approx}, which is calculated by Eqs. (1)-(15) given in Section 2.

The training and test sets consist of data samples, where one sample contains one combination of the values of the original input parameters, the calculated k_{approx} for the given input combination and the corresponding target value of the coupling coefficient k obtained by precise simulations in the full-wave EM simulator.

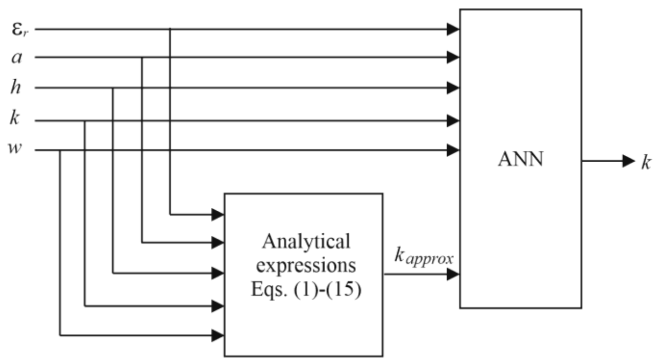


Fig. 3 Proposed PKI neural model of microstrip coupled resonator coupling coefficient

5. Results and Discussion

The proposed approach has been applied to model the microstrip coupled resonator coupling coefficient by exploiting the same data used in [6] for developing the black-box neural models aimed to predict the coupling coefficient for the given resonator dimensions and the properties of the substrate, $k = (a, w, s, h)$, for the constant value of ε_r. In Table 1 the considered ranges of the input dimensions as well as the considered values of ε_r are given.

The training set has consisted of 2089 samples covering all four ε_r values, whereas the validation test set has consisted of 40 samples not used in the training set. Several ANNs with different number of hidden neurons were trained and the best model has been obtained with the ANN having two hidden layers, each containing 17 neurons. The ATE, WCE and r values for the training set and the test set are given in Table 2. The corresponding scatter plots showing the correlation of the predicted and target values for the training and test sets are given in Fig. 4.

Table 1 Considered ranges/values of the input parameters

Parameter	Range/Values
a	(5 - 20) mm
w	(0.1 – 4) mm
s	(0.1 – 3.5) mm
h	(0.254 - 1.575) mm
ε_r	2.33, 4.4, 6.15, 10.2

Table 2 Test statistics for the training and the test sets

Set	ATE[%]	WCE[%]	r
Trainig set	0.5	2	0.99967
Test set	0.24	2.55	0.99981

Table 3 Comparison of the predicted and target values for ten chosen test samples

k - target	*k – ANN model*	AE	RE[%]
0.096523	0.097757	0.001234	1.28
0.082074	0.082802	0.000728	0.89
0.066264	0.065804	0.000460	0.69
0.068744	0.066463	0.002280	3.32
0.073213	0.074809	0.001596	2.18
0.066295	0.065904	0.000390	0.59
0.074939	0.075631	0.000692	0.92
0.070582	0.070506	0.000075	0.10
0.058675	0.059139	0.000464	0.79
0.047486	0.047668	0.000183	0.38

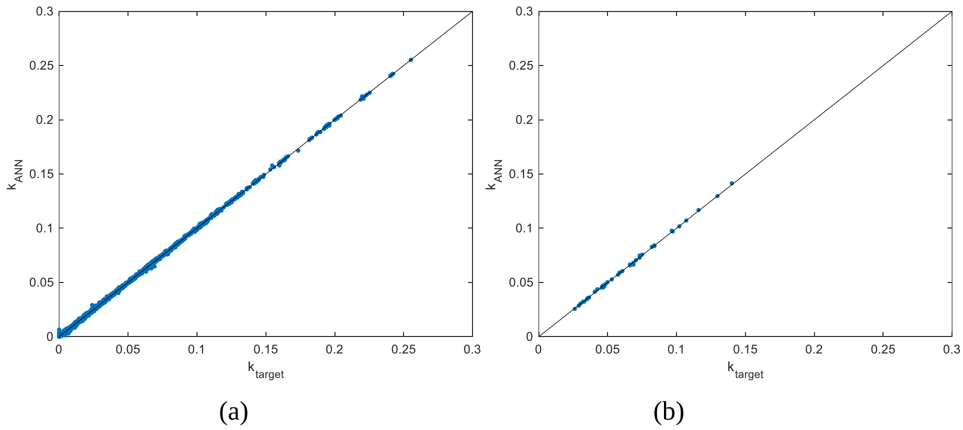
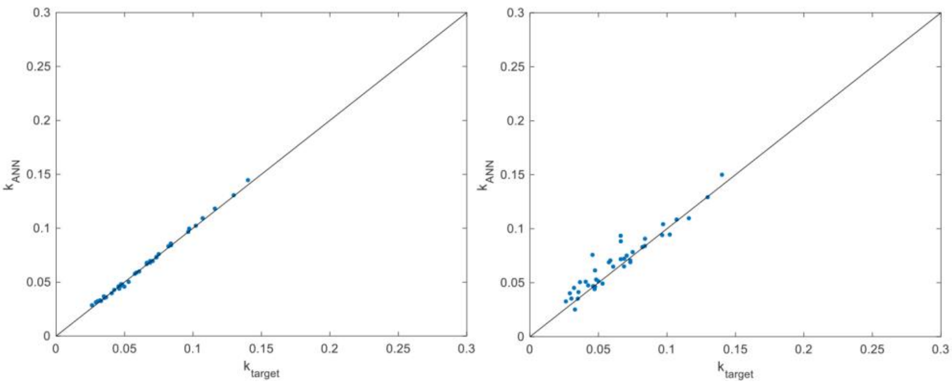


Fig. 4 Correlation of the ANN generated coupling coefficient and the reference target values (a) training set, (b) test set

Small errors in predicting both training and test values, as well as a good correlation, show that the proposed model not only learnt well the training data but has a good generalization accuracy on the test set not seen by the ANN during the training phase.

As an additional illustration, in Table 3, for ten randomly selected test samples, the target and predicted values are reported together with the corresponding absolute errors (AE - the absolute difference of the predicted and target values) and the relative errors (RE - the AE devided by the target value and expressed in percent). The rest of the test samples shown the similar errors. The relative errors are mostly below 2%, which can be considered as a good predicting accuracy.

This model includes the dependence of the coupling coefficient on the relative dielectric constant, which was not possible to achieve with a simple black-box model by using the available data, i.e. without increasing the training set. To investigate how much the training set can be downsized in order to keep the same level of accuracy of the proposed model additional analysis have been performed. With this aim, the training set has been reduced but removing certain data samples, taking care that all considered areas of the input space were properly represented.



(a) (b)

Fig. 5 Correlation of the ANN generated coupling coefficient and the reference target test values for the models trained with the (a) training set of 873 samples, (b) training set of 692 samples

The proposed model has been developed for each reduced size training set ensuring the same level of training accuracy as in the initial case. The models have been further tested on the same test set (consisting of 40 samples) used for testing the model developed by using the full training set. The process of downsizing the training set has been stopped when the accuracy in predicting the test values started to get worse. In total, the test has been performed with four data sets consisting of 1230, 1036, 873 and 692 data samples. The test statistics is shown in Table 4.

Table 4 Test statistics for the test set obtained by the models trained with the reduced size training sets

Training set	ATE[%]	WCE[%]	*r*
Reduced – 1230 samples	0.93	5.48	0.998672
Reduced – 1036 samples	1.01	4.20	0.998495
Reduced – 873 samples	1.05	3.90	0.998728
Reduced – 692 samples	6.25	26.47	0.952975

It can be seen that the accuracy of the first three models is very similar. However, for the last data set, although the model was well trained, the correlation with the target test values has significantly decreased, which is confirmed by the higher errors. This can be clearly seen from Fig. 5, where the scatter plots of the predicted data versus the target data for the last two data sets, containing 873 and 692 samples, show much higher discrepancies between the predicted and the target values of the coupling coefficient. It can be concluded that the number of training data can be more than halved comparing to the considered initial training set. This further means that the proposed approach can be exploited to develop the model for determining the coupling coefficient a much smaller number of the training data than the pure black-box model.

6. Conclusion

In this paper a novel modeling procedure exploiting prior knowledge neural approach is proposed for accurate determination of the coupling coefficient of a microstrip coupled resonator. Unlike the black-box neural approach, which assumes that an ANN is exploited to model the coupling coefficient dependence of the filter geometry and substrate properties, in the proposed model, an additional input of the ANN is a value of the coupling coefficient obtained by mathematical expressions for approximate calculation of the coupling coefficient, representing the prior knowledge for the ANN. By introducing the prior knowledge, the number of needed samples in the training data is reduced, that mean that less time is needed to acquire the training data by the time consuming EM simulations, making the whole process of the model development more efficient and faster.

Comparing to the black-box model, the proposed model needs significantly less training data to develop the model with the desired accuracy. Moreover, it gives a good accuracy in the cases where the black-box approach would need much more data to be exploited. In the considered case, with the available training data, the model includes dependence on the relative dielectric constant, which was not possible to achieve with a pure ANN model.

The model provides values of the coupling coefficient which are very close to the target values obtained by the EM simulations. As the ANN can be described by a set of mathematical expressions based on the basic mathematical operations and exponential function, the ANN response can be calculated in a very short time. Consequently, the ANN accompanied with can the expressions representing prior knowledge be used for instant prediction of the coupling coefficient. In other words, the proposed model can be successfully used as a fast and accurate replacement of the EM simulation for the coupling coefficient determination.

Looking from the side of the expressions used as the prior knowledge, which are used for approximate determination of the correlation coefficient, the ANN can be seen as an addition to these expressions improving their accuracy.

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