Design of Wideband Non-equiripple Filtering Response Using Genetic Algorithm Based Neural Network

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Abstract— In this paper, the wideband multiple-mode-based bandpass filter with non-equiripple response is designed using genetic algorithm based neural network. The neural network is first employed to reduce the complexity in the design of wideband in-band equiripple response. Without deriving analytic solutions or solving non-linear equations, the coefficients of polynomials for the filters with non-equiripple responses can also be determined. Finally, the filters with both the five-pole equiripple and non-equiripple bandpass responses are designed and demonstrated. The accuracy of the proposed optimization method is also discussed in details.

1. INTRODUCTION

Ultra-wideband technology has been receiving much attention since the frequency range from 3.1–10.6 GHz was licensed for commercial communication applications by the Federal Communications Commission (FCC) in 2002. Thus, many researchers have explored different kinds of wideband bandpass filters with a fractional bandwidth of 110%. For the wideband filter design, some synthesis approaches have been developed based on the transmission line theory [1, 2]. However, these approaches were required to deal with the expressions of traditional *Chebyshev* functions and $ABCD$ matrices. For the high-order filter with more transmission poles, the derivation becomes very complicated. In addition, the initial *em* simulated frequency responses of these synthesized filters are always poor and unpredictable, especially near the transition band due to the existing frequency dispersion and parasitic effects. This situation will probably get worse if the additional manufacturing errors are involved.

To remedy this issue, the *Chained-function* was employed as a transfer function in [3]. The insertion loss near the edge of the passband can be set to be smaller than that in the center of the passband, which is useful for reducing the sensitivity to the manufacturing errors. After that, a dome-shaped envelope filtering function in [4] provided an alternative solution to the *Chained-function* filter.

Very recently, a wide-band dome-shaped envelop filtering function was formulated. By computing the coefficients of the polynomials, a wide passband with non-equiripple response can be achieved [5, 6]. Nevertheless, this method still needs repetitive calculations of unknown coefficients for different specified ripple levels. To reduce the computational complexity, the numerical process based on neural network is proposed here to find these coefficients according to the filtering specifications. In general, the transfer functions for both equiripple and non-equiripple responses can be expanded as a polynomial with unknown coefficients. Thus, the forming transfer function becomes how to determine these coefficients.

In this paper, the genetic algorithm (GA) is used to optimize the learning process in the neural network [7], which can be trained to obtain the unknown coefficients for the required transfer function. This network is first trained to achieve equiripple *Chebyshev* response to prove its accuracy. Then, it can be extended to obtain the coefficients for the non-equiripple response, instead of solving the complicated non-linear equations in our previous study [5, 6]. The results show that this approach is accurate enough for the design of the wide-band bandpass filter and also efficient for the synthesis purpose.

2. DESIGN OF WIDEBAND FILTERING RESPONSES

To show the whole process for the proposed design approach, a single multiple-mode-resonator (MMR) bandpass filter with transmission poles is modeled. Fig. 1(a) shows the equivalent transmission line model of this filter. Here, the optimal design process has only one-step with neural network instead of the traditional two steps design approach with expressions of $ABCD$ matrix and *Chebyshev* functions. The flow charts of the two design processes are shown in Fig. 1(b) and Fig. 1(c), respectively.

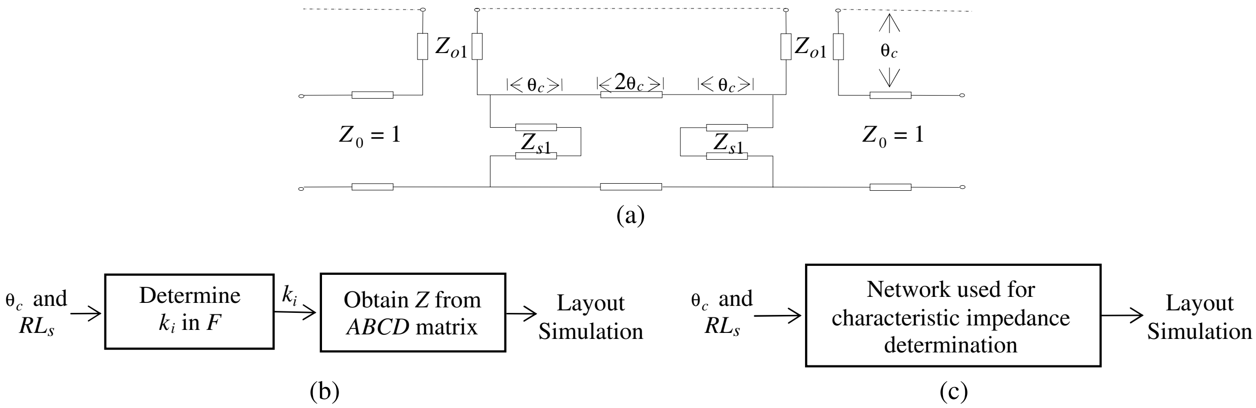

Figure 1: (a) Transmission-line model of a five-pole multiple-mode-based bandpass filter. (b) Flow chart of traditional design. (c) Flow chart of neural network based design.

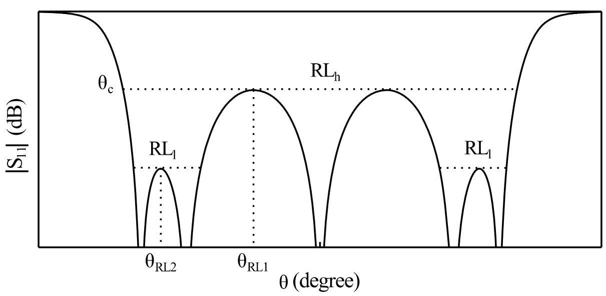

Figure 2: Reflection coefficients of a wideband bandpass filter with non-equiripple response.

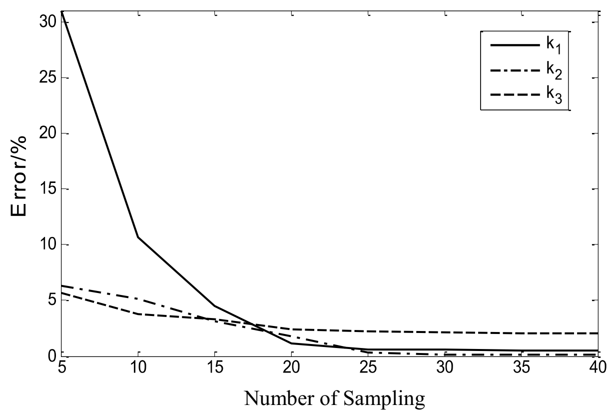

Figure 3: Training errors of network versus the number of sampling.

Traditionally, the characteristic impedances of each transmission line section can only be obtained from the $ABCD$ matrix after matching the coefficients of the transfer function F with *Chebyshev* function. Hence, the neural network can be trained to determine the coefficients. Next, we can also train the network to obtain the characteristic impedances.

According to the filter specifications, the cut-off frequency (θ_c) and the in-band reflection lobes (RL) as shown in Fig. 2 can beset as the samples of input vectors, while the coefficients k_i of filtering transfer function are set as the output vectors in the network training process. For all the network training process, the maximum training step is set to 2000 and the target error is zero. As shown in Fig. 3, the accuracy of the trained network can be enhanced by increasing of the number of the sampling data. It can also be noticed that the training error converges well when the number of the samples is larger than 25.

2.1. Equiripple Responses with Five Transmission Poles

For a five-pole *Chebyshev* bandpass filer with equiripple response, F can be derived as [1]

$$F = k_1 \frac{\cos^4\theta}{\sin\theta} + k_2 \frac{\cos^2\theta}{\sin\theta} + k_3 \frac{1}{\sin\theta} \tag{1}$$

Here, we can define the input vector according to the filter specifications as

$$P = \left[\begin{array}{cccc} \theta_c^1 & \theta_c^2 & \cdots & \theta_c^{31} \\ RL^1 & RL^2 & \cdots & RL^{31} \end{array} \right] \tag{2}$$

where $\theta_c \in (10°, 70°)$ and $RL = -20\,\text{dB}$. And the output vector is defined as

$$T = \begin{bmatrix} k_1^1 & k_1^2 & \dots & k_1^{31} \\ k_2^1 & k_2^2 & \dots & k_2^{31} \\ k_3^1 & k_3^2 & \dots & k_3^{31} \end{bmatrix} \tag{3}$$

where $n = 31$ in this case, and $k_{i=1,2,3}$ is the three unknowns of coefficients in (1). Table 1 shows the trained and analytically derived coefficients, and their relative errors. It can be noticed that the errors from the training are less than 2.1% in comparison with the results from the analytical solutions in [1]. It implies that the trained network can also achieve a good performance. Also, the frequency responses with the trained coefficients from the neural network have a good agreement with those obtained from analytical solutions.

Table 1: Trained results for five-pole bandpass filter with equiripple responses ($\theta_c = 45°$ and $RL = -20\,\text{dB}$).

Coefficients	Synthesis [1]	Trained	Errors
k_1	5.6284	5.5962	0.572%
k_2	−3.8799	−3.8808	0.023%
k_3	0.5828	0.5948	2.059%

2.2. Non-equiripple Responses with Five Transmission Poles

Different from the filter with equiripple responses, the unknown coefficients for the filter with non-equiripple responses cannot be derived analytically. Instead, we have to solve non-linear equations [6], where the design procedure becomes complicated. Thus, it would be interested to extend the aforementioned training process based on neural network to the filter design with non-equiripple responses. For this purpose, the coefficients for equiripple response filter can be adjusted within a small range to generate new sampling coefficients for the non-equiripple responses. With these new coefficients, the insertion loss and the return loss can also be determined. Subsequently, a set of cutoff frequency θ_c, the higher ripple constant RL_h and the lower ripple constant RL_l can be obtained as sampling points.

For the non-equiripple bandpass filter with five transmission poles, the input vector can be written as

$$P = \begin{bmatrix} \theta_c^1 & \theta_c^2 & \dots & \theta_c^{50} \\ RL_h^1 & RL_h^2 & \dots & RL_h^{50} \\ RL_l^1 & RL_l^2 & \dots & RL_l^{50} \end{bmatrix} \tag{4}$$

where the two reflection lobes may have different ripple-level constants RL_h and RL_l. Similarly, the output vector can beset as the same as (6), while the input vectors are the $\theta_c \in (10°, 70°)$, $RL_h \in (-21, -10)\,\text{dB}$ and $RL_l \in (-26, -20)\,\text{dB}$. Fig. 4 shows the non-equiripple frequency responses of the designed filter based on the trained network.

The target and obtained network values for the parameters θ_c, RL_h, RL_l are tabulated in Table 2. The dotted lines indicate the target parameters θ_c, RL_h and RL_l. The error obtained from the trained network is about 3.68% for the ripples near the band edges, while the error near the center of band is about 0.20%, as shown in Table 2.

Table 2: Trained results for five-pole bandpass filter with non-equiripple responses.

Parameters	Target	Obtained	Errors
θ_c	0.5233	0.5292	1.13%
RL_h	−20.0000	−20.0394	0.20%
RL_l	−25.0000	−25.9212	3.68%

3. OPTIMIZATION FOR FILTER IMPLEMENTATION

Traditionally, in order to implement the above filter, the characteristic impedances of transmission line sections can then be determined via $ABCD$ matrices, as detailed in [1]. However, this synthesis procedure involves two steps: finding coefficients and determining the impedances. Based on the

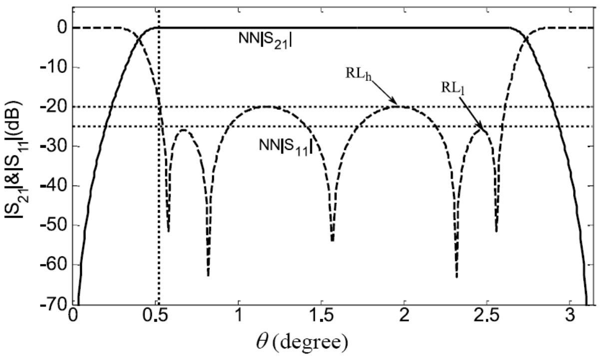

Figure 4: Frequency response $|S_{21}|$ and $|S_{11}|$ of the five-pole bandpass filter obtained from trained networks for non-equiripple responses, with $\theta_c = 30°$, $RL_h = -20\,\text{dB}$ and $RL_l = -25\,\text{dB}$.

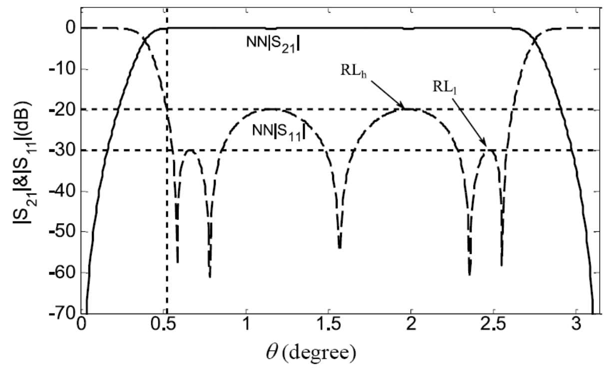

Figure 5: Frequency responses of the filter obtained from one-step training for non-equiripple responses ($\theta_c = 30°$, $RL_h = -20\,\text{dB}$ and $RL_l = -30\,\text{dB}$).

neural network optimization, this design procedure can also be simplified by omitting the first step with finding coefficients. Details of these two design procedures are shown in the flow chart of Figs. 1(b) and 1(c). Let's consider the filtering topology in [1] as an example. The input vector for the training initialization still contains three parameters, i.e., θ_c, RL_h and RL_l, as those defined in (7). The output vector of the training network can be set directly with the characteristic impedances in the transmission line model, i.e., z_{o1}, $z^1_{1,2}$, and z_{s1}, which is given by

$$T = \begin{bmatrix} z^1_{o1} & z^2_{o1} & \dots & z^{75}_{o1} \\ z^{1,1}_{1,2} & z^{1,2}_{1,2} & \dots & z^{1,75}_{1,2} \\ z^1_{s1} & z^2_{s1} & \dots & z^{75}_{s1} \end{bmatrix} \tag{5}$$

Here, the sampling data with both the equiripple responses and non-equiripple responses are considered in the training process. Fig. 5 shows the trained results for filters with non-equiripple responses. As shown in Tables 3 and 4, the overall errors for the case with equiripple responses are less than 1.2%, while the errors are well controlled within 0.5% for the case with non-equiripple responses.

Table 3: Trained results for filter with equiripple responses.

Parameters	Target value	Network value	Error
θ_c	0.7850	0.7857	0.08%
RL_h	−20.0000	−19.8748	0.63%
RL_l	−20.0000	−20.2365	1.18%

Table 4: Trained results for filter with non-equiripple responses.

Parameters	Target value	Network value	Error
θ_c	0.5233	0.5234	0.01%
RL_h	−20.0000	−19.9051	0.47%
RL_l	−30.0000	−29.9713	0.10%

4. CONCLUSION

In this paper, the GA-based neural networks have be enutilized in the design of the wideband bandpass filter. Instead of deriving complicated expressions in the traditional way, the design parameter can be easily obtained with a well robust control. In addition, the proposed method can be directly extended to obtain the design parameters for the filter with non-equiripple responses, where the traditional synthesis cannot be applied analytically. As shown in the given samples, the overall errors for the final design are well controlled. Without any intermediate computation, the training process has been applied to obtain the characteristic impedances in the transmission line model.

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