A NEW SYNTHESIS ALGORITHM FOR MIXED LUMPED-DISTRIBUTED LOW-PASS LADDER NETWORKS VIA ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this study, a new synthesis algorithm for mixed lumped-distributed low-pass ladder networks via artificial neural networks is presented. In the course of algorithm, first, a neural network which has a single hidden layer consists of 15 neurons is formed and by using 500 examples, it is trained to calculate the component values of the 5th degree mixed lumped-distributed circuit. An example is included to exhibit the implementation of the proposed synthesis algorithm and it is seen that the obtained values via the algorithm are very close to the values that are calculated by using conventional synthesis procedures.

I. INTRODUCTION

Synthesis techniques for the lumped element networks are valid at all frequencies. However, as the design frequency increases, it becomes more difficult to realize the lumped elements necessary to fabricate the circuit. Internal parasitics, which may be negligible at lower frequencies, cause significant deviations from the anticipated characteristics, resulting in hardware performance that deviates markedly from that expected.

In addition, it is assumed that voltage and current is not a function of distance from the terminals of a lumped element. That is, the impedance is independent of physical length. When the size of the element is an appreciable fraction of a wavelength, the voltage and current is a function of distance from the connection points, and the element can no longer be considered lumped. It is difficult to define a particular size where the lumped assumption begins to deteriote; most designers have a rule of thumb based on experience with specified elements, types of circuits, and fabrication methods. Even if components can safely be considered lumped at the design frequency, the high-frequency response may be degraded, which can result in unacceptable out-of-band characteristics.

These problems can be avoided by designing with distributed elements; that is, cascaded transmission lines and transmission lines terminated with an open or short, known as a unit element (UE) in synthesis theory, which turns out to be extremely important for physical realizability.

II. SYNTHESIS OF CASCADED UNIT ELEMENTS

The input impedance of a transmission line terminated with an arbitrary load z_L can be written as

$$z_{in} = z_C \frac{z_L + j z_C \tan\theta}{z_C + j z_L \tan\theta} = z_C \frac{z_L + z_C\lambda}{z_C + z_L\lambda} \qquad (1)$$

Let $z(\lambda)$ be the driving-point impedance of a network consisting of shorted stubs $z_{si}\lambda$ and open stubs z_{oi}/λ, which is positive real and rational in λ. Then, when a transmission line element is cascaded, the input impedance becomes

$$z_{in}(\lambda) = z_C \frac{z(\lambda) + z_C\lambda}{z_C + z(\lambda)\lambda} \qquad (2)$$

which is also positive real and a rational function in λ. Working backwards, it can be evaluated $z_{in}(\lambda)$ at $\lambda = 1$:

$$z_{in}(\lambda)\big|_{\lambda=1} = z_{in}(1) = z_C \frac{z(1) + z_C \cdot 1}{z_C + z(1)\cdot 1} = z_C \qquad (3)$$

which provides the characteristic impedance of the transmission line element directly from the input impedance.

Richards' Theorem: A unit element of characteristic impedance $z(1)$ can always be extracted from a positive real rational impedance $z(\lambda)$ leaving a remainder of

$$z'(\lambda) = z(1)\frac{z(\lambda) - \lambda \cdot z(\lambda)}{z(1) - \lambda \cdot z(\lambda)} \qquad (4)$$

which is also rational and positive real of degree at most equal to that of $z(\lambda)$. Furthermore, if

$$Ev\{z(1)\} = 0$$

i.e., the even component of $z(\lambda)$ evaluated as $\lambda = 1$ equals 0, then

$$\deg\{z'(\lambda)\} = \deg\{z(\lambda)\} - 1.$$

III. SYNTHESIS OF LUMPED LOW-PASS LADDER NETWORKS

Consider the ladder networks with inductive series branches and capacitive shunt branches (low-pass) shown in Fig 1. Input impedance of the circuits is $z(p)$ (input reflection factor is $s(p)$), where p is the usual complex frequency variable ($p = \sigma + jw$). The first element is either a series inductor or a shunt capacitor, depending on whether $z(p)$ or $y(p)$ has the pole at infinity.

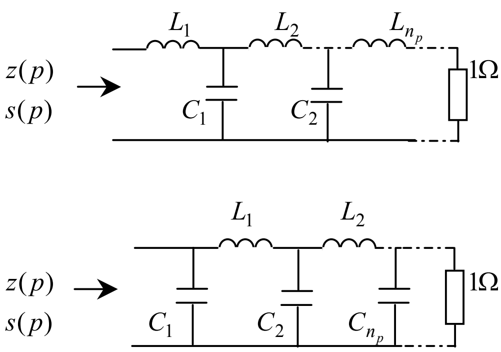


Figure 1 Low-pass LC ladder networks

Algebraically, the networks just discussed (first Cauer structure) corresponds to a continuous fraction expansion about the point at infinity,

$$z(p) = a_1 p + \cfrac{1}{a_2 p + \cfrac{1}{a_3 p + \cfrac{1}{a_4 p + \dots}}} \quad (5)$$

The a_i are always residues at infinity and can be determined by an iterative long division procedure, in which at each step the remainder is divided into the divisor of the previous step.

IV. MIXED LOW-PASS LADDER NETWORKS

From the physical implementation point of view, one practical circuit configuration is that of simple low-pass ladder sections connected with unit elements (LPLUE) as shown in Fig. 2

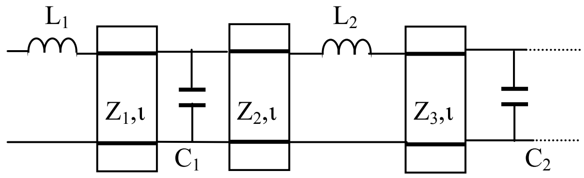


Figure 2 Low-pass ladder with unit element

The scattering matrix describing the mixed element two-port can be expressed in the Belevitch canonical form as [5],

$$S(p,\lambda) = \frac{1}{g(p,\lambda)} \begin{pmatrix} h(p,\lambda) & \sigma f(-p,-\lambda) \\ f(p,\lambda) & -\sigma h(-p,-\lambda) \end{pmatrix} \quad (6)$$

where

- $f(p,\lambda)$ is a monic real polynomial that consist of transmission zeros,
- $h(p,\lambda)$ ve $g(p,\lambda)$ are real polynomials in the complex variables $p = \sigma + jw$ and $\lambda = \varepsilon + j\Omega$ ($\lambda = \tanh(p\tau)$, τ being the delay length of unit elements),
- $g(p,\lambda)$ is a Scattering Hurwitz polynomial,
- σ is a unimodular constant; $|\sigma| = 1$,
- Losslessness of the mixed element two-port requires that

$$g(p,\lambda)g(-p,-\lambda) = h(p,\lambda)h(-p,-\lambda) + f(p,\lambda)f(-p,-\lambda).$$

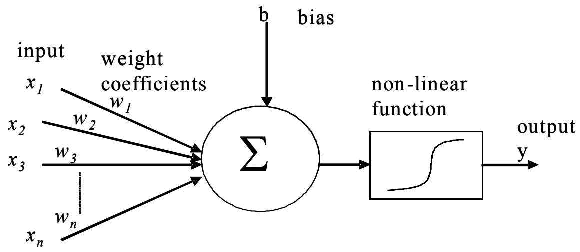
The first rows of h and g matrices are used to synthesize distributed part of the network, and the first columns are used to get the component values of lumped part. Other elements of the matrices give connectivity information that can be used to calculate transducer power gain (TPG) of the network.

V. NEURAL NETWORKS

Artificial neural networks (ANN) which consist of simplified neurons connected to each other are the models of nervous system. Although each neuron has a simple function alone, they can be used to solve complex problems, when they are used together.

Artificial neural networks are adaptive systems which have learning capabilities. ANNs adapt and organize themselves to the changing conditions, improve a function and make the calculation by learning. ANNs can produce the correct response even though missing or corrupted input is given to them. They are more suitable for the daily life problems because of their nonlinear characteristics [11].

In Figure 3, a neuron can be seen which consists of a summing junction and a non-linear activation function. Here, x_1, x_2, …,x_n are inputs; w_1, w_2,…, w_n are synaptic weight coefficients and y is output.



$$u=w_0x_0+w_1x_1+w_2x_2+\ldots+w_nx_n$$

$$y=f(u+b)$$

Figure 3 Neuron model

A neural network model can be seen in Figure 4. Each neuron has many inputs and only one output, and this output is the input for the other neurons, so system is formed in parallelly.

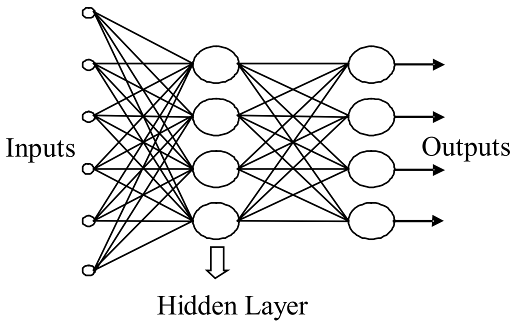


Figure 4 ANN with one hidden layer

ANNs can be used in signal processing, image processing, pattern recognition, medical, military systems, finance systems, artificial intelligence and power systems.

5.1. Learning in Artificial Neural Networks

Learning in artificial neural networks is based on the calculation of the synaptic weight coefficients suitable for the problem. Learning rule is an equation set by which all or some of the synaptic weight coefficients change so as to modify the response of each neuron in time. By this way ANN can adapt itself to get the desired response.

ANNs are learnt by example data instead of programming. Learning process can be divided into two groups; supervised and unsupervised learning.

In supervised learning, both the input and the response are given to the system. For each input, obtained response and desired response are compared. To get the minimum difference, synaptic weight coefficients are changed. When an acceptable error is obtained, learning process is stopped and then these synaptic weight coefficients can be used with the data that are not used in learning process.

5.2. Back Propagation Algorithm [13]

In this paper, back propagation algorithm is used as the learning algorithm, which has emerged as the most widely used and successful algorithm for the design of multiplayer feedforward networks.

In learning process, first of all, an error is obtained by subtracting the result from the desired value. Then the error is squared. In this algorithm, it is desired to realize a learning process with an error whose square is minimum.

$$\varepsilon^2 = (t-y)^2 \qquad (7)$$

$$\varepsilon = \varepsilon(y(u(w))) \qquad (8)$$

Then delta values are calculated at the output nodes.

$$\nabla_w \varepsilon^2 \equiv \frac{\partial \varepsilon^2}{\partial w} \qquad (9)$$

And by using back propagation, all the values at the output nodes are calculated.

$$\begin{aligned}\nabla_w \varepsilon^2 &= \frac{\partial \varepsilon^2}{\partial y} \cdot \frac{\partial y}{\partial u} \cdot \frac{\partial u}{\partial w} \\ &= -2\,\varepsilon\, sgm'(u)x \\ &= 2\,\delta\, x\end{aligned} \qquad (10)$$

$$\delta \equiv -\varepsilon\, sgm'(u) \qquad (11)$$

Finally, the components of gradient are calculated and desired synaptic weight coefficients are obtained.

$$\Delta w = -2\,\mu\,\delta\, x \qquad (12)$$

$$w_{old} = w_{new} + \Delta w \qquad (14)$$

VI.EXAMPLE

In this study, a neural network which has a single hidden layer consists of 15 neurons is formed and by using 500 examples, it is trained to calculate component values of a 5th degree mixed lumped-distributed low-pass ladder network (two unit elements and three lumped elements).

h and g matrices of the mixed network and the networks itself are given below,

$$h=\begin{bmatrix} 0 & 1.2249 & -0.9753 \\ -0.1602 & -0.2537 & -1.7483 \\ 0.0858 & -3.0093 & 0 \\ -0.8582 & 0 & 0 \end{bmatrix} \quad g=\begin{bmatrix} 1 & 2.5088 & 1.3968 \\ 1.8550 & 4.8501 & 1.7483 \\ 1.7078 & 3.0093 & 0 \\ 0.8582 & 0 & 0 \end{bmatrix}$$

$\tau = 0.1535$

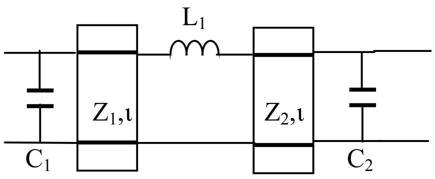


Figure 5 Designed mixed circuit

By using ANN, the component values are calculated as
C1=0.9431, C2=1.1610
L1=1.6346
Z1=1.0881, Z2=2.7657

Also, by using conventional synthesis techniques, the component values are obtained as
C1=0.9570, C2=1.0583
L1=1.6948
Z1=1.1072, Z2=2.6264

Let's calculate TPG of the network via these two sets of component values;

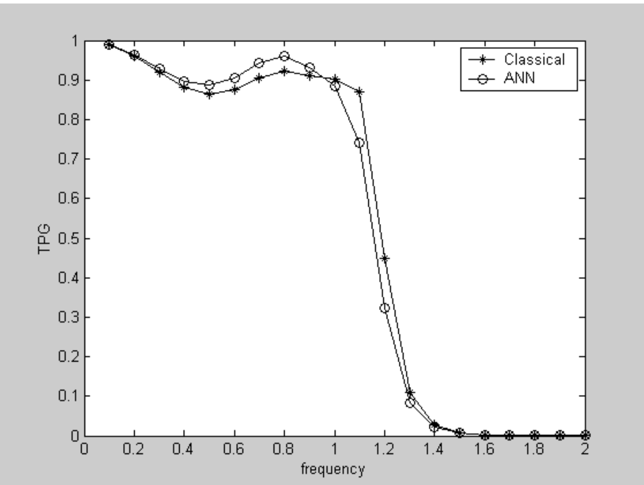


Figure 6. TPG curves versus frequency

VII. CONCLUSION

As one can see from the example, component values are very close to the values that are obtained by using classical synthesis routines. As a result between the TPG curves there is a small difference. This error can be made smaller if ANN is trained better, say longer training set, smaller or different learning procedures. As a result of this study it can be said that ANN can be trained to synthesise the mixed lumped-distributed circuits.

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