# A SMITH CHART REPRESENTED BY A NEURAL NETWORK AND ITS APPLICATIONS

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## ABSTRACT

The Smith chart, while being a very useful graphical tool for the analysis and design of high frequency circuits, is subject to manual interpretation errors. A normalized impedance and admittance chart (Y-Z Smith chart) represented by a neural network type distributed computing system is developed for design automation. Two examples showing the use of such a neural network to design an impedance matching circuit are presented.

## INTRODUCTION

The analysis of transmission-line problems and of matching circuits at microwave frequencies is generally tedious in analytical form. The Smith chart provides a very useful graphical tool to these problems. However, the manual interpretation of the Smith chart can be error prone. This project is, to the best of our knowledge, the first attempt to represent a normalized impedance- and admittance-coordinate Smith chart (Y-Z Smith chart) by a neural network. Examples of using this neural network to determine an impedance matching circuit are demonstrated.

The objective of this research is to automate the analysis of a Smith chart. Recently, neural networks have gained their popularity as a special form of parallel computer [1]. Neural networks are formed by interconnecting many simple processors (neurons). In contrast to conventional parallel computers, the function of each neuron is simple, and the overall behavior is determined predominantly by the set of interconnections. Although neural networks are famous for their capability to *learn* the solutions to the problems that they are designed to solve, they also provide a framework for constructing specialized parallel machines to solve specific problems. For example, a neural network designed to solve the travelling salesman problem, which represents a class of combinational optimization problems, is proposed in [2].

## NEURAL NETWORK SMITH CHART

Figure 1 shows a Y-Z Smith chart. For the sake of description, only constant-resistance and constant-conductance circles are shown in Figure 1. All constant-resistance circles are shown with solid lines and all constant-conductance circles are shown with dotted lines. Also, only a sufficient number of circles for the explanation of this novel representation are provided. The technique to be described can be readily extended to any desired precision by adding circles to the Y-Z Smith chart.

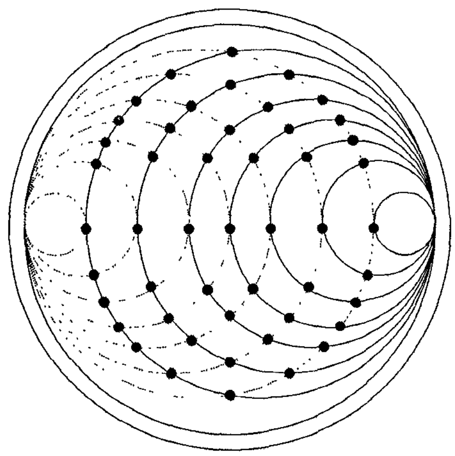

Figure 1 Neuron placement on a Y-Z Smith chart.

The resistance and conductance circles intersect with each other and form a set of cross-over points on the Y-Z Smith chart. A neuron, called an intersection neuron in the following discussion, is placed on each of these intersections. We will first describe the function of a neuron to be used in this technique. Figure 2 shows a neuron with n inputs ($i_1$ - $i_n$) and one output (K). An input can be excitatory (indicated by a solid circle) or inhibitory (indicated by a hollow circle) and is assigned a weighting factor $W_j$. A threshold value, T, is associated with the neuron. The function of the neuron is quite simple. It simply uses the following equation to generate an input value I,

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$$I = \sum_{j=1}^{n} W_j * i_j, \quad (1)$$

where $W_j$ is positive for an excitatory input and negative for an inhibitory input. If I is above the threshold value T, the neuron fires and produces an output of K = 1. Otherwise, the neuron remains idle and outputs a K = 0. A neuron is also associated with a time constant ($\tau$) that determines the latency between the time when its inputs change and the time that it fires.

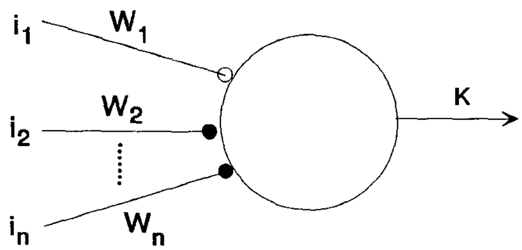


Figure 2 The structure of a neuron.

Two ways of representing the Y-Z Smith chart by a neural network will be shown. In order to show the structure of the neural network that is used to represent the Y-Z Smith chart and the detailed interconnections, it is mapped to rectilinear graphs as shown in Figures 3 (version 1) and 8 (version 2). For easy visualization, only a portion of the upper half of the Smith chart (i.e., positive reactance) is provided in these Figures. A complete implementation can be easily derived from Figure 1.

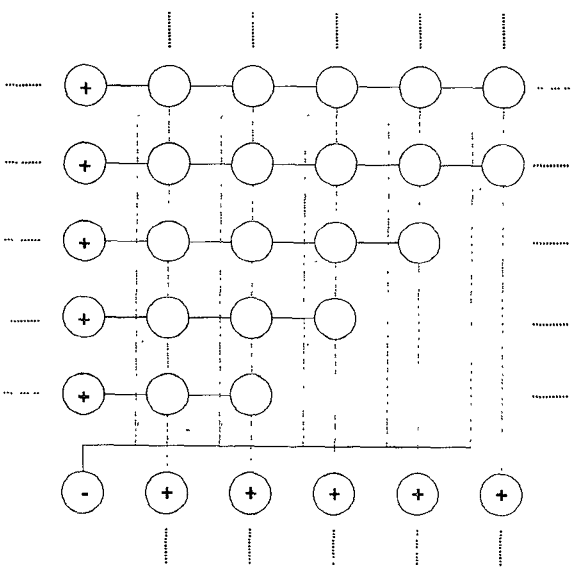

Figure 3 The Y-Z Smith chart neural network mapped to a rectilinear graph (version 1).

In the first version implementation of Figure 3, all the neurons in a row/column excite each other. For clarity, this mutual excitatory relationship is shown in Figure 3 as connecting a row/column to a summing unit (+) which sends their sum back to all contributing neurons as an excitatory signal. The equivalence between these interconnections is shown in Figure 4. All neurons also have an external input (not shown) which can be set by the user. Furthermore, a global inhibitory neuron (-) is associated with all neurons. The relationship between an inhibitory neuron and its associated neurons is shown in Figure 5.

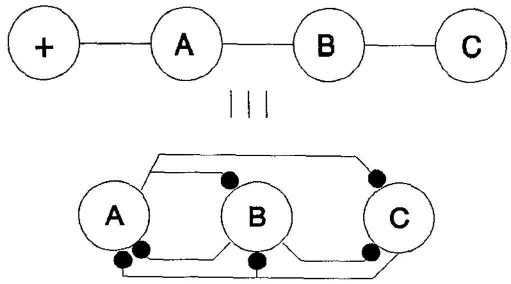


Figure 4 The relationship between a summing unit and its associated neurons.

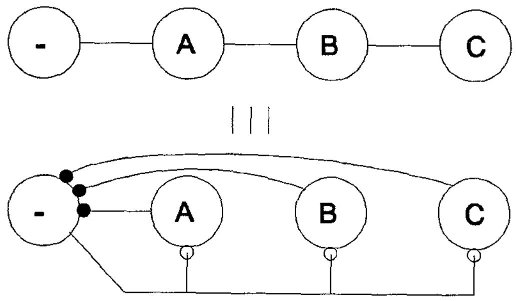


Figure 5 The relationship between an inhibitory neuron and its associated neurons.

To demonstrate the application of the neural network Y-Z Smith chart in Figure 3, it is used to determine an impedance matching circuit for an impedance 0.2+j0.2. In this example, the weighting factors and threshold values for the neural network are given in Table 1.

The locations of all neurons in the Y-Z Smith chart are known. However, for convenience of explanation, the neurons will be identified by their coordinates (x, y) in the following discussion, where x and y are the column and row numbers, respectively. For example, the intersection neuron at the lower left corner has coordinates (1, 1). The neurons at (2, 2) and (5, 4), representing the impedances $Z_1$ = 0.2+j0.2 (starting impedance) and $Z_o$ = 1 (impedance to be matched), respectively, are identified in the neural network. An input signal of 1 is applied to the external inputs of these two neurons at time t = 0. After the time constant $\tau$, these two neurons fire (i.e., turn on). The summing units of row 2 and column 2 provide a sum of 1 to all neurons in this row and this column, respectively. Meanwhile, the summing units of row 4 and column 5 also provide a sum of 1 to all neurons in this row and this column, respectively. These sums have no effect on the neurons except the one that is at (2, 4), which will receive an input of 2 and fires at $t = 2\tau$. The firing of this neuron boosts the outputs of the summing units at column 2 and row 4 to 2. These summing unit outputs turn on the neurons on the row/column at $t = 3\tau$. A snapshot at $t = 3\tau$ is shown in Figure 6, in which the neurons in column 2 and row 4 are fired.

Table 1 Parameters for the neural network shown in Figure 3.

| | |
|---|---|
| Threshold value of an intersection neuron | 1.9 |
| Threshold value of the inhibitory neuron | 3.8 |
| Timing constant of an intersection neuron | $1\tau$ |
| Timing constant of the inhibitory neuron | $0.5\tau$ |
| **Weighting Factors** | |
| an external input -> an intersection neuron | 2 |
| a summing unit -> its associated neurons | 1 |
| an intersection neuron -> the inhibitory neuron | 1 |
| the inhibitory neuron -> its associated neurons | -1 |

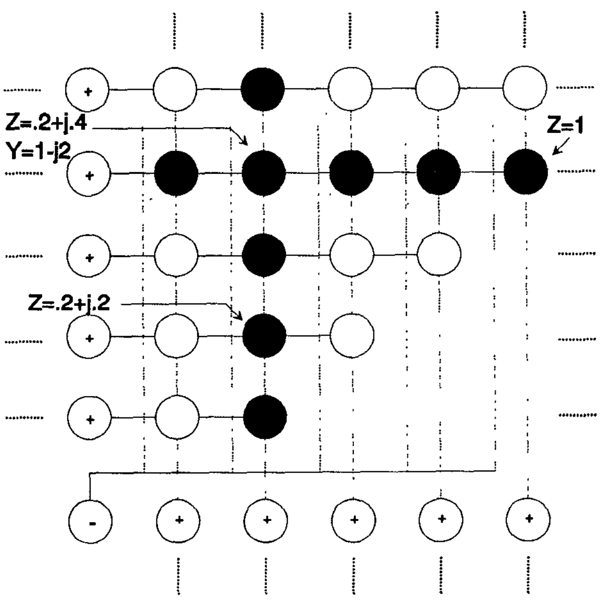


Figure 6 A snapshot of Figure 3 at $t = 3\tau$.

It can be easily seen from Figure 6 that any intersection neuron now has a minimum input value of two and hence all neurons will be turned on. The inhibitory neuron is provided to solve this problem. Due to its threshold value, the inhibitory neuron remains idle when less than 4 neurons are fired. The multiple neurons on the fired column and row raise the inhibitory neuron input to a value beyond its threshold. An inhibitory signal is then sent to all intersection neurons. Because of the smaller time constant of the inhibitory neuron, the inhibitory signal will stop the neurons stayed off up to this point from being turned on. This inhibitory signal has no effect on the fired column and row since it is outweighted by multiple excitatory signals. The network is now at a stable state.

Tracing a path consisting of the fired neurons between neurons (2, 2) and (5, 4) will identify neuron (2, 4) as a turning point. The location of this neuron on the Smith chart determines the topology and value of impedance/reactance that should be added to the circuit. The result of this impedance matching circuit is shown in Figure 7.

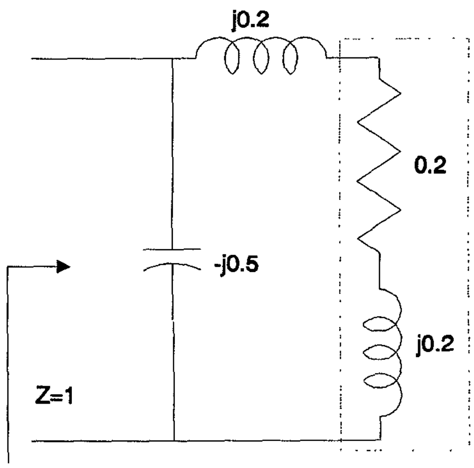


Figure 7 The impedance matching circuit.

The neural network shown in Figure 3 does indeed give the correct impedance matching circuit. However, the neuron at the intersection of firing column and row needs to be located manually by tracing them. In addition, a global inhibitory neuron is needed which may make the implementation difficult. These drawbacks can be eliminated by the second version of a neural network Smith chart shown in Figure 8. In Figure 8, each neuron actually includes a display neuron (D) and a calculation neuron (C). All the C-neuron outputs in a row/column are connected to a summation unit ($\Sigma$) which sends the result to all D-neurons in the same row/column as an excitatory signal. This is equivalent to exciting the receivers of the summation unit by all its contributing C-neurons. Figure 9 shows this equivalence relationship. Each pair of D- and C-neurons share a common external input (not shown) which can be set by the user. This neural network is used to solve the same impedance matching problem described above. The parameters for this neural network are given in Table 2.

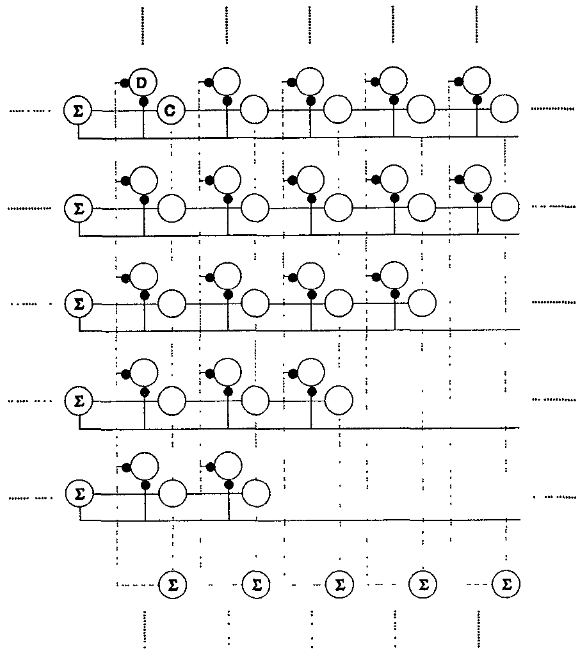


Figure 8 The Y-Z Smith chart neural network mapped to a rectilinear graph (version 2).

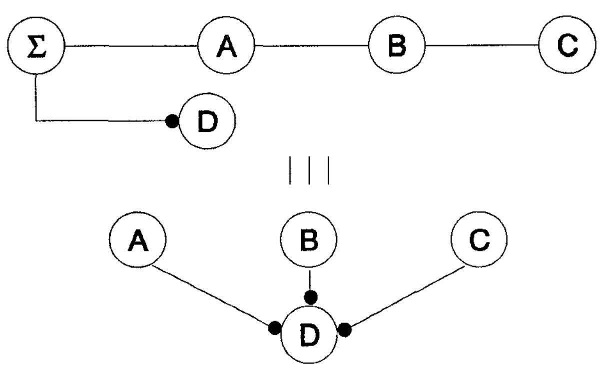


Figure 9 The relationship between a summation unit and its associated neurons.

Table 2 Parameters for the neural network shown in Figure 8.

| | |
|---|---|
| Threshold value of a D-neuron/C-neuron | 1.9 |
| Timing constant of a D-neuron/C-neuron | $1\tau$ |
| **Weighting Factors** | |
| an external input -> a D-neuron/C-neuron | 2 |
| a summation unit -> a D-neuron | 1 |

In Figure 8, the D- and C-neurons at both locations (2, 2) and (5, 4) are turned on at $t = \tau$ by external inputs. The summation units of column 2 and row 4 will turn on the D-neuron at (2, 4) which indicates the impedance matching result. This is shown in Figure 10. While the result is identical to that of the first version, the neuron (2, 4) is identified automatically in the D-neuron layer.

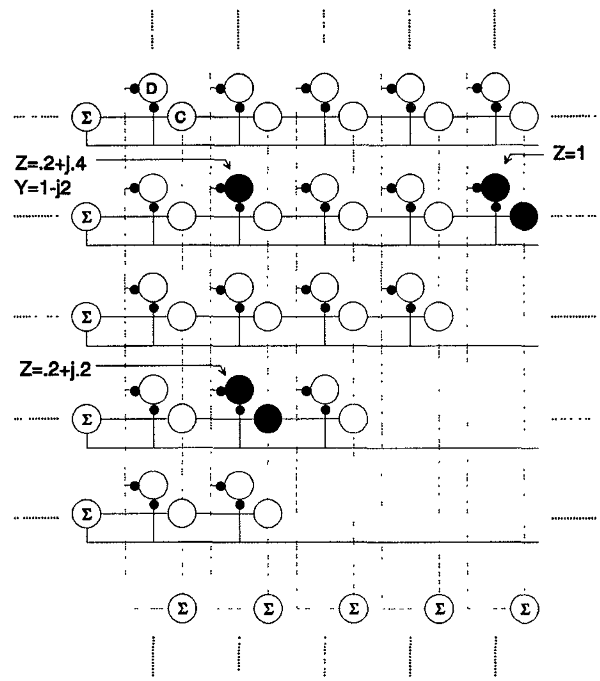


Figure 10 A snapshot of Figure 8 at $t = 2\tau$.

## SUMMARY

In summary, a novel neural network representation of the Smith chart is developed. Two examples showing how this neural network can be used to solve the problem of impedance matching were given. This technique can be extended to other analyses based on a Smith chart such as optimizing the noise figure and the gain of an amplifier.

## REFERENCES


[1] R. P. Lippmann, "An introduction to computing with neural nets," *IEEE ASSP Magazine*, pp. 4-22, April 1987.

[2] J. J. Hopfield and D. W. Tank, " "Neural" computation of decisions in optimization problems," *Biological Cybernetics*, vol. 52, pp. 141-152, 1985.