Neural control of smart electromagnetic structures

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ABSTRACT

We are studying a new class of smart structures—smart electromagnetic structures (SEMS). These structures are "smart" in that they integrate sensing elements (e.g.,antennas), processing elements (neural networks) and control elements(diodes) in a manner not previously considered. Smart Electromagnetic Structures(SEMS) have the potential to provide an adaptive electromagnetic(EM) environment for the structure on which they are mounted. Based on their sensing capabilities they may be able to detect and modify the surrounding EM fields and thus modify the far field image of their structure. The ability to adapt derives from the closed loop nature of the SEMS, hence the speed of adaptation is determined by the speed of the loop. The speed of the system response is determined primarily by the speed of the computational elements. The implementation we are studying includes an Artificial Neural Network(ANN) as the processor. The SEMS loop can respond at a rate of three gate delays for each iteration of the loop if it is implemented in parallel hardware. We have found that the network requires three to five iterations to complete its control task. This leads one to believe the total time for a response is less than or equal to fifteen gate delays. In silicon technology this would result in a response time of approximately 750 n secs. With GaAs technology the response time would be reduced to 15 n secs. Even with a dedicated digital implementation of a neural network a response time of 450 microseconds would be possible. This speed would be suitable for many existing applications.

Artificial neural networks(ANNs) and their ability to model and control dynamical systems for smart structures, including sensors, actuators, and plants, are directly applicable to the SEMS concept[1]. The application of neural networks to the area of controls is being reported frequently[2]. The ability of a structure to adapt to impinging electromagnetic(EM) energy will allow the structure to change its reflection characteristics and thus to change its radar signature[3]. By embedding a control element in the structure of a single microstrip patch element[4a,4b], its electrical characteristics can be changed. If such an element can be controlled by a closed loop system the patch antenna element can be made to adjust its operating characteristics through the control algorithm. If the control algorithm can be implemented in a neural network, the system can be made to change its characteristics in response to the stimulus. This change can be used to alter the antenna's performance in real time. As part of our research, a model of the patch neural network antenna system is being developed and this analytical model, as well as experimental models of the antenna are being tested and compared. The neural network antenna model and prototypes are being taught to adapt to the magnitude and phase response of microstrip patch antennas to incoming signals. The response characteristics and speed are reported in this paper. We demonstrate that the patch can be given autonomous adaptive capabilities using neural networks. An array of such smart patches could be assembled to create an even more adaptable antenna system.

2. The Neural Net Antenna

The micropatch antenna has been the mainstay of conformal antennas for many years[5]. The antenna has many advantages including simplicity and size, and a few drawbacks, e.g., narrow bandwidth. The electrical characteristics of the antenna can be adjusted using control elements embedded in the patch itself[6]. We will describe research being carried out in the Autonomous Systems Laboratory(ASL) of Florida Institute of Technology(FIT) into the control of such patch antenna elements using a neural network (NN) in the feed back loop to enhance the operating characteristics of the patch. The advantages of a neural net over a classical processor and algorithmic control scheme are that the net has the potential to be taught by example, rather than requiring the calculation of new control points for each new condition. The neural net has the advantage of being able to make the required determinations in near real time. The additional ability of the net to adapt to previously unknown inputs (generalization) and its fault tolerance

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makes the neural antenna an ideal candidate for flexible tactical antennas for the future. In addition, the antenna could be manufactured with a set of control devices placed at convenient points on the patch surface. The network could then determine the configuration of these points necessary to achieve the desired tuning effect after manufacture thus reducing the effect of manufacturing tolerance on the performance of the antenna.

The combination of a simple neural network with a microstrip patch antenna shown in Figure 1 has the potential to enhance the characteristics of the patch antenna. An example of this is center frequency tuning which will be described in this paper.

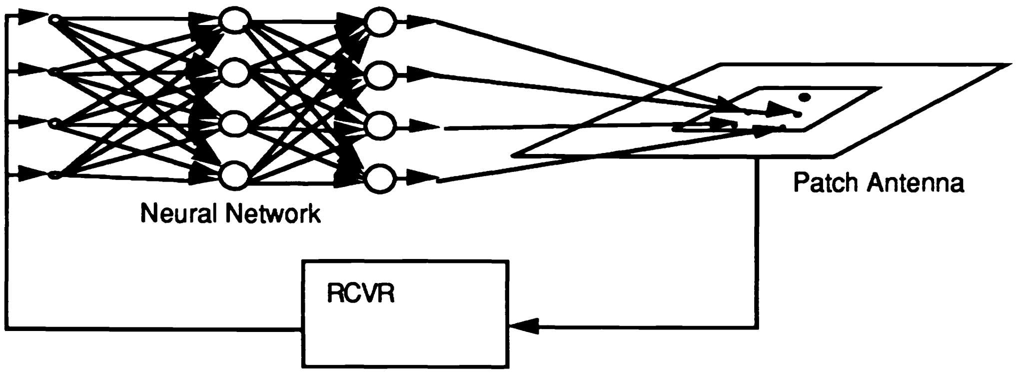

Figure 1. The microwave patch antenna with tuning points and a neural network to drive the points can be considered a smart antenna structure.

With a combined NN and antenna it becomes possible to "retrain" the antenna when and if performance requirements change. The trained network will respond rapidly to changing electromagnetic conditions. Typically one gate delay per layer of the network is required for the system to adapt to new conditions. The number of layers may vary, but two or three layers is sufficient for all problems[7]. The network will therefore be able to adapt in near real time (ca. 30-70 nsec) to a changing environment. The training of the antenna during the fabrication phase can take place on deliverable equipment so that the antenna can further be adapted to the specific environment in which it will operate (e.g. VSWR, signal level, frequency, boresight angle, etc.) This allows the NN antenna system to adapt to changes in environment. Training time depends on the type of network and training algorithm chosen but would be achieved "off line."

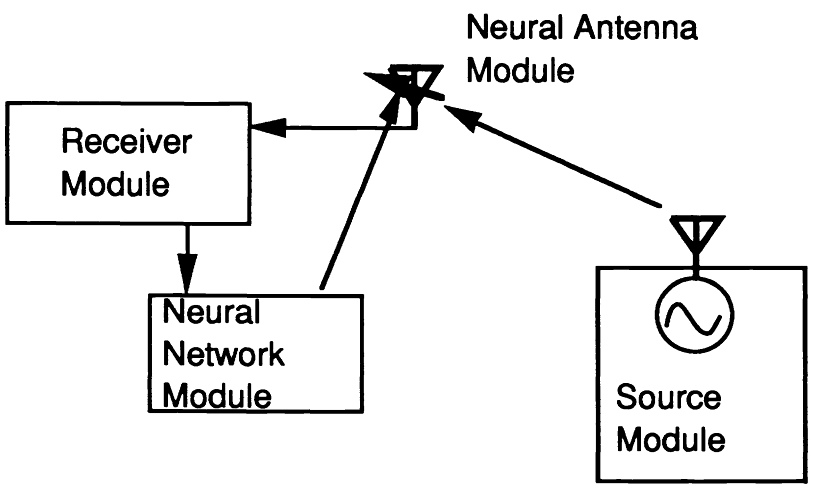

Figure 2 Block diagram of the software simulation of a single patch with a single tuning varactor installed.

2.1 Neural Network Tracking for the Smart Antenna

The fundamental power of the neural net antenna resides in the ability of the neural processor to learn to control the antenna and in the case of frequency control to move the antenna center frequency(bias voltage) to coincide with the frequency of the stimulating source. A model of the neural antenna system was constructed using the C language on a Macintosh IIx. The block diagram of the simulation system is shown in Figure 2.

The receiver model is a simple I and Q channel coherent receiver. The neural network is a Jordan type network with memory. Figure 3 shows the diagram of the network.

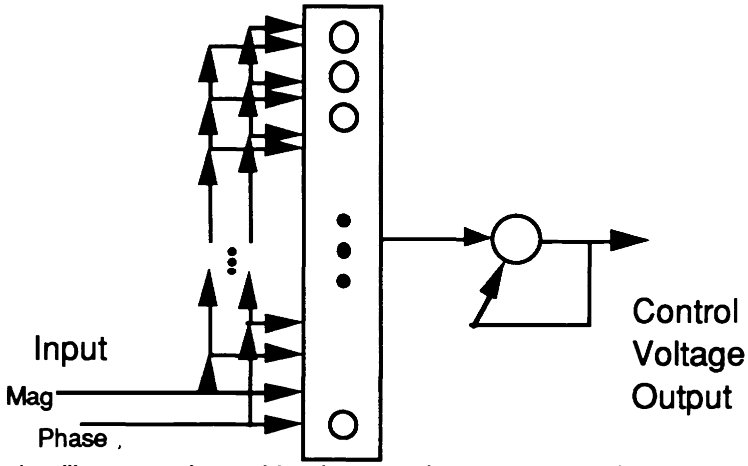

Figure 3 The Jordan like network used for the neural antenna control processor.

2.2 Neural Network Model

Our first goal in training the smart antenna structure is to provide high-speed frequency tracking of an unknown incoming signal. The system which is composed of tunable antenna, a neural network controller and receiver performs this function. The closed loop antenna element is trained to optimize the antenna function within the system.

The network described consists of two layers, fourteen neurons in the input layer and twenty neurons in the hidden layer. One neuron is in the penultimate layer. Each neurons uses a sigmoidal squashing function allowing an numerical output ranging from +1 and -1.
One linear neuron with fixed weights and an integrating connection is used for the output of the network.

Conventional neurons with a sigmoid squashing function, configured in a Jordan multi-layer neural network are used. Two neurons in the input layer receive sensor information from the receiver, the rest of the input layer neurons receive delayed values in a shift register fashion from their neighbor. There are a total of seven pairs of neurons in the input layer.

For training a conventional back-propagation algorithm was used to adapt the weights. Since the input layer has time-delayed input values, we wait to change the weights until all input neurons have received an actual input from a given test pattern. The strategy for training will be described in more detail in section 4.

3. The Smart Antenna Concept

The neural network must determine the proper bias voltage for the tuning element embedded in the antenna to tune the antenna center frequency to coincide with the unknown incoming signal frequency. Figure 4 shows the change in center frequency due to change in input voltage for the tunable patch antenna.

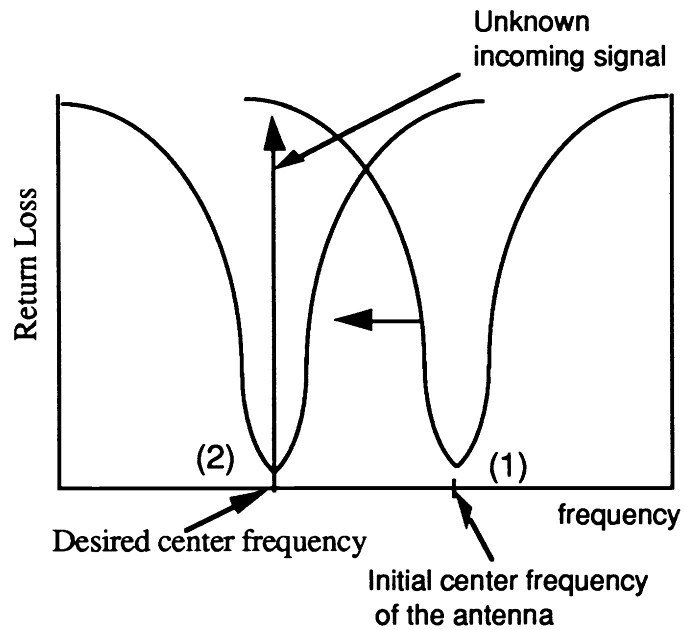

Figure 4. Relationship between the center frequency and unknown incoming signal frequency.

An antenna whose center frequency can be varied by changing the bias voltage on a device embedded in the antenna was first described by Schaubert[6]. We apply this concept to move the center frequency of the antenna from position (1) to position (2) by applying the proper bias voltage which is determined by the neural network.

First we must develop an algorithm to train the sequential neural network to do this. We must choose a subset of the total training set to use for training the net. We explain the training strategy in section 4.

4. Training Algorithm

The neural network was trained with a conventional back-propagation(BP) algorithm. The basic BP algorithm was modified to include a strategy for choosing the input training patterns and for calculating the error terms. Input values for the neural network came from the receiver. The target value were determined at the output of the neural network. Target values were determined by subtracting accumulated voltage from the desired target voltage.

We initially chose four different pairs of diode voltages as training patterns [initial bias values,desired bias values; (5v,25v), (10v,20v), (20v,10v), and (25v,5v).

A step by step description of the training process is given below;

Step 1. Initialize all input neurons, weights, and offsets.
Set all input neurons, weights, and node offsets to small random values.

Step 2. Choose an input pattern at random.
Set the receiver output to an initial bias voltage randomly chosen from the training set,

Step 3. Apply the input and propagate it forwards through the network,
The output of the individual neurons within the network are calculated as shown below;

$$o_i(t) = f(net_i(t))$$

Where net_j is define as;

$$net_i \begin{cases} = \sum_j I_j \cdot W_{ij} & \text{for hidden neurons} \\ = \sum_k O_k \cdot W_{ik} & \text{for output neurons} \end{cases}$$

and f describes the squashing function.

Step 4. Determine the desired output

For our network the time course of the system results in the bias voltage that corresponds to the final tuning frequency of the antenna being presented at the output of the network. The constraint that this time function must be well behave is implied. The input and desired pattern will be changed at every iteration of the network. We choose a desired output as a value which make the difference between accumulated voltage and a target voltage zero.

$$\begin{aligned} T_i(t) &= AV(t) - TV \\ &= (O_i(t) + AV(t-1)) - TV \end{aligned}$$

where, **AV**(t)=accumulated voltage at time t

TV= target voltage used for a given initial starting voltage.

For a better understanding how to decide the desired output, we show a graph of accumulated voltage vs. time. Figure 5. shows the untrained network response for a starting input diode voltage of 20v and target voltage of 10v, the graph shows 30 iterations of the network (epochs).

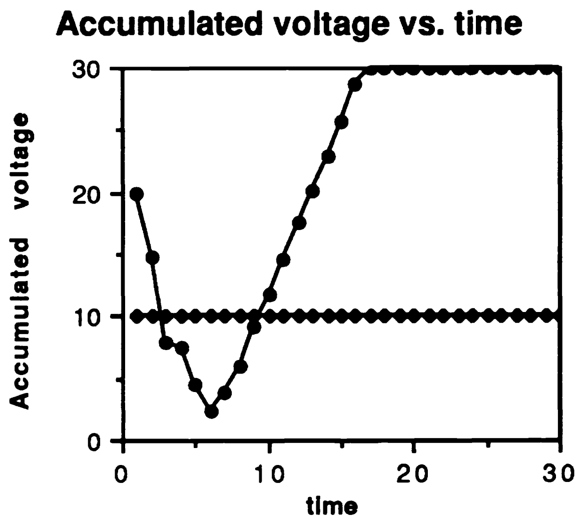

Figure 5. Plot of accumulated voltage and target voltage(10v) vs. time without training.

With a starting voltage of 20V. and the target of 10 volts the untrained network was well behaved for only eighteen epochs. The error can be seen as the difference between the desired value(a constant 10 volts) and the actual net output(e.g. a t=9 the error is approximately zero.) After 18 epochs the output saturates and no further change information is available. The desired response of the system would be for the output to go directly from 20 volts to 10 volts in one step. This would provide an ideal step response with no overshoot or ringing. For the epochs before the system saturates the error values can be measured and used for back propagation. Figure 6 show the output of the penultimate neuron for the above session. Since there has been no training, the output value looks like a random walk until the system saturates.

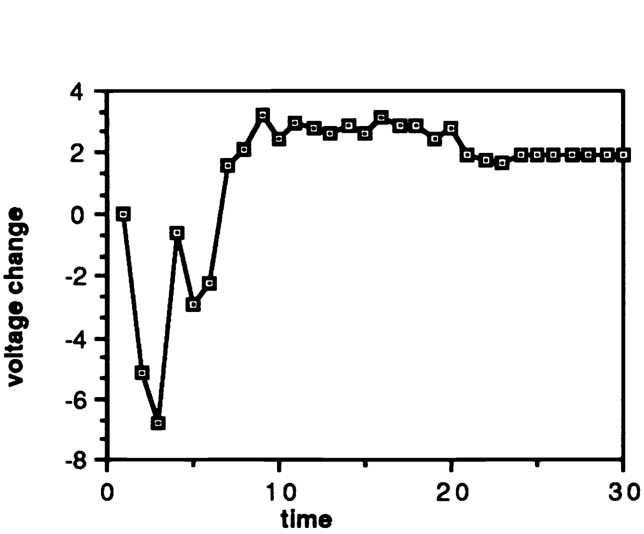

Figure 6. Plot of voltage variation on the penultimate neuron.

Step 5. Compute the change of the weights using back-propagation rule.

Weight changes are computed by the relation;

$$\Delta W_{ji}(t+1) = \eta \delta_j O_i + \alpha \Delta W_{ji}(t)$$

Where η is the learning rate of the network and δ is given by ;

$$\delta_{pj} = \frac{\partial E_p}{\partial net_{pj}}$$

and α is the momentum. E_p is the error function for the network. For further discussion of the learning algorithm see Rummelhart [8].

Step 6. Calculate the new input

Based on the tuning voltage determined by the network the receiver and antenna system output is determined. For a detailed description of the model see Thursby, et al [9], Drici, et al[10].

Step 7. Repeat step 3 through 6 during response time.

The response time is defined as the time from the start of the stimulus until the system has reached steady state or has caused the system to saturate.

Step 8. Update all weights

The weight change is computed after a complete response has been obtained. The weights are calculated as follows. For each epoch ***l*** the difference between the desired output and the actual output is used to determine the weight change for each epoch. After the weight changes for all epochs have been accumulated, the average weight change for each weight is calculated;

the average weight change for the weight between neuron ***l*** and ***k*** for pattern ***l*** given by,

$$\left[\Delta w^{i}_{lk}\right] = \frac{1}{N} \sum_{i=1}^{N} \Delta W^{i}_{lk}$$

Change the weights with averaged weight changes using

$$W_{lk}^{new} = W_{lk}^{old} + \left[\Delta w_{lk}\right]$$

Repeat steps 2 through 8 until the error is reduced to an acceptable level.

The error is defined as;

$$E = \sum_j (T_j - O_j)$$

5. Results Of Training.

The system was trained to respond to four different starting and target frequencies. The final error in training was less than 0.05%. The network converged to similar error values for several different initial weight sets. Thus the configuration seems to be stable. Figure 9 shows the results of training the network to produce the desired response.

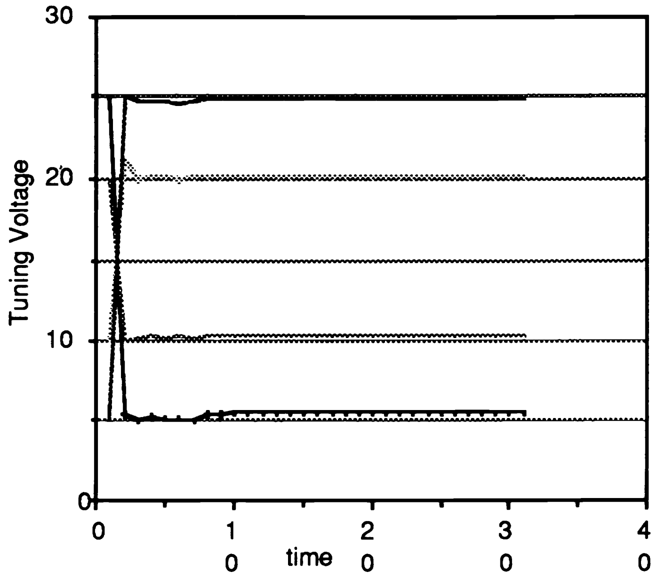

Figure 9 Results of training network to tune the antenna.

Figure 10 shows the results of several tests of initial and final values that were not used for training. The ability of the antenna system to tune to the desired center frequency is demonstrated by the rapid movement from the starting voltage to the desired final voltage.

6. Further Test Results

Because of the inherent non linear nature of the system we have investigated the response of the trained network from several points of view. First the network response to different initial conditions for a fixed target should not change significantly over the operating range of the system. To test this we presented the system with several different initial conditions for a given target value.

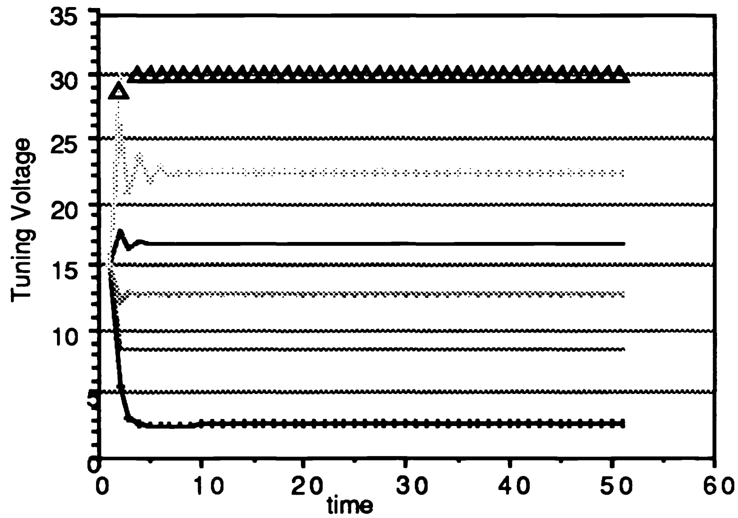

Figure 10 Results of testing the trained neural antenna with previously untested conditions.

The response of the system to these conditions is shown in figure 11. Four different target voltages 5v,10v,20v, and 25v, were chosen for this set of tests. Regardless of which starting voltage we choose, the system converge to the desired target voltage in four or fewer iterations.

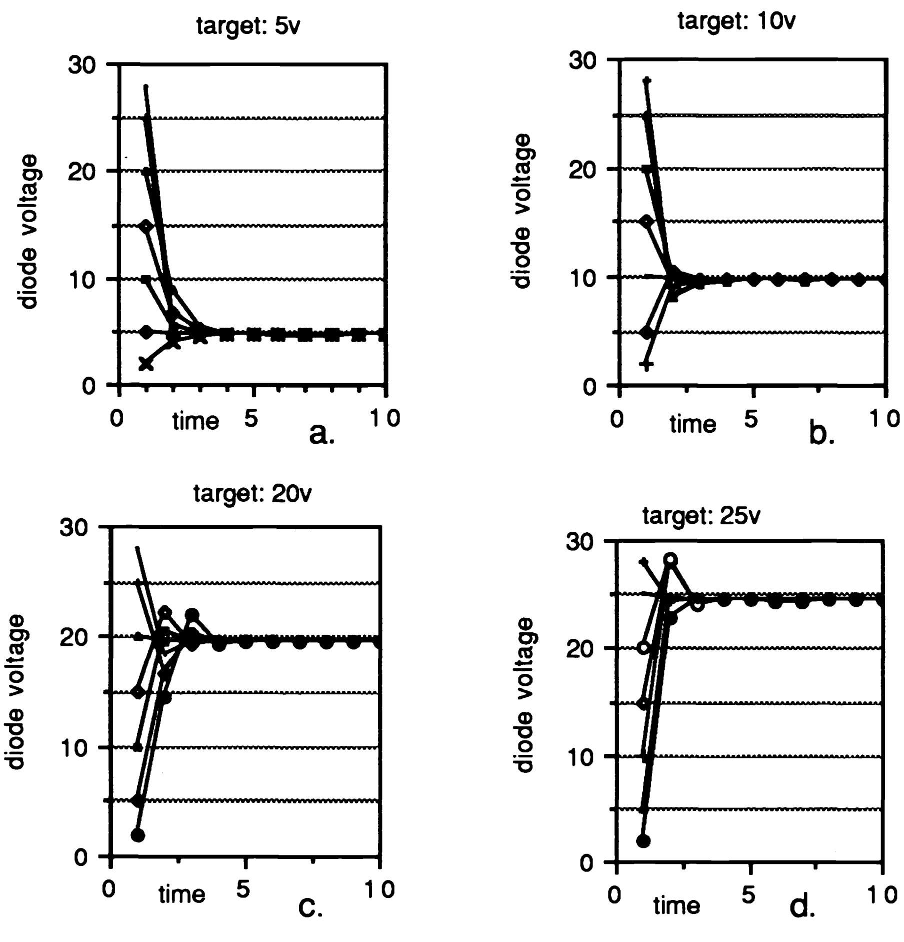

*Figure 11.*Response of the network with training patterns.

The second case of interest is one where the input condition is held constant and the desired output is varied over the range of operation of the system. This corresponds to the actual operating range of the embedded control device. Figure 12 shows results of test cases where different target voltages were used to test the network with the same starting voltage (15v).

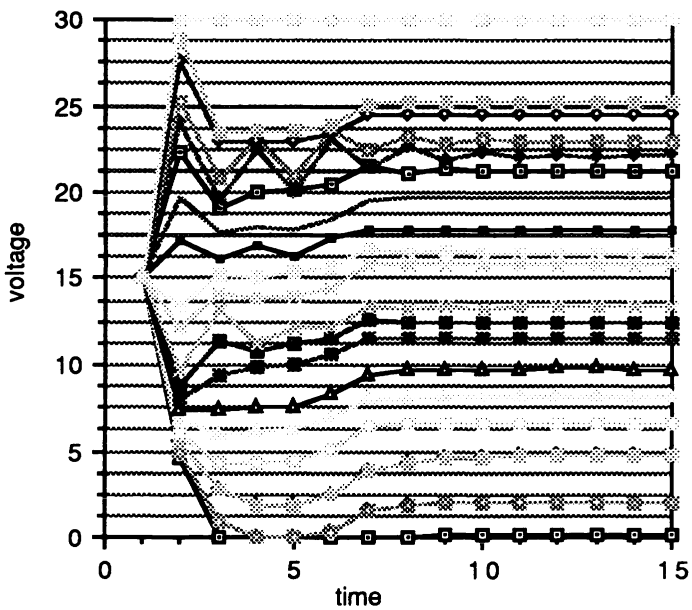

Figure 12. Test result for non-trained target voltage.

The steady state error of the network when compared with the desired tuning voltage is shown in Figure 13

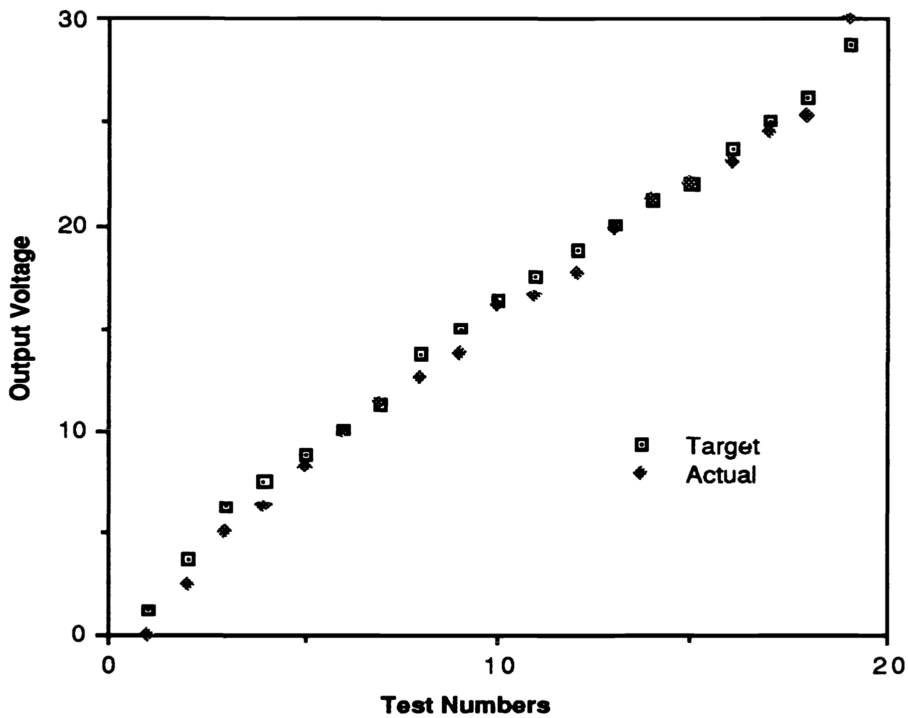

Figure 13 The error produced by the neural antenna system over the set of test cases shown in Figure 12.

Figure 13 shows that the error from the desired response of the system is well contained and centers around the desired response.

We have also tested the system against a linearly changing input frequency for the unknown input signal. Both positive and negative sloped frequency characteristics have been tested. The response of the system to a positively increasing frequency signal is shown in Figure 14.

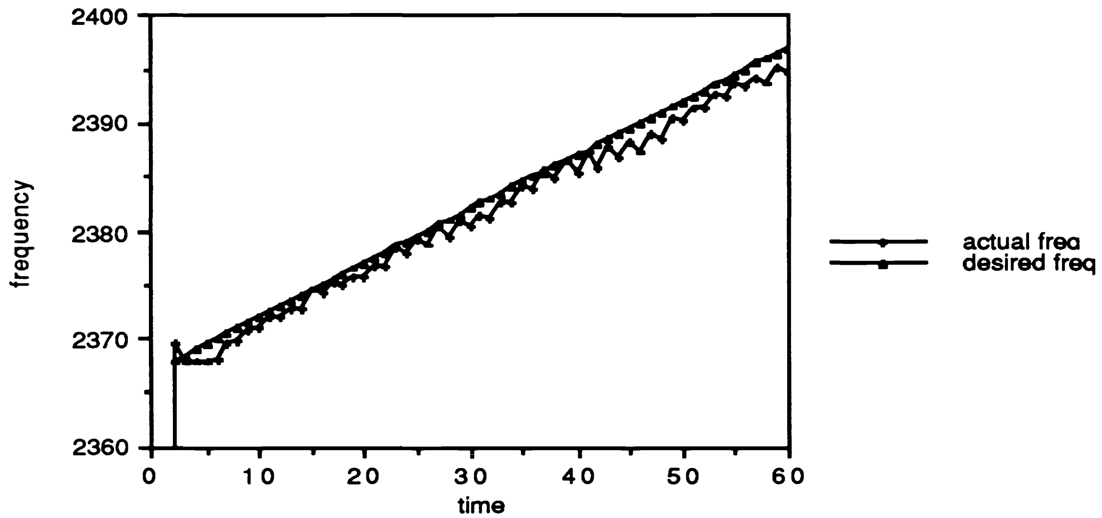

Figure 14. System response for linearly sweeping target frequency.

For slower sweep rates the response of the network is seen to be a step, with the network waiting for a threshold to be crossed before compensating further for the change of frequency. As the slope increases the step sizes decreases and the graph shown in Figure 14 demonstrates an almost continuous updating of the output in response to the input signal. The greater the slope the better the network is able to track the input.

7. Conclusion

We have demonstrated an antenna system controlled by a neural processor that can tune its operating frequency to optimize its response to an incoming signal in near real time. The network is relatively simple and contains only thirty six neurons. The use of a fixed weight integrating neuron was found to improve the response of the network. The network responded with less than 0.05 % error to the training set and when tested with data previously not seen the system responded with error less than 12%, as measured with respect to the desired amplitude. The system was able to respond to a dynamically varying velocity input signal with minimal steady state error. Although this neural network was used to control the smart antenna, the concept of delayed input value and accumulated weight change can be applied to many control problem area.

8. Acknowledgements

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