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Time series cross prediction in a single transistor chaotic circuit using neural networks

M. P. Hanias*,[1] and L. Magafas[2]

[1]*Technological and Educational Institute of Chalkis, GR 34400, Evia, Chalkis, Hellas*

[2]*Department of Electrical Engineering, Kavala Institution of Technology, St. Loukas 65404 Kavala, Hellas.*

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Abstract

In this paper we will be trying to cross predict a multivariate time series of a single transistor chaotic circuit using neural networks. For this purpose we investigate the influence of a number of first and second order near neighbors in predicting chaotic time series using a back propagation neural network. This influence is examined by changing the number of neurons in the hidden layer of a backprogation neural network with one hidden layer. The number of neurons at the input layer were equal to the embedding dimension of the corresponding strange attractor.

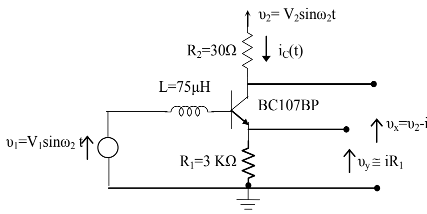
Keywords: Chaos, neural networks, time series prediction, electronic circuits.

1. Introduction

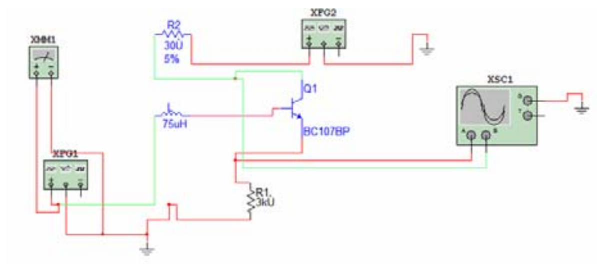
In certain number of previous papers, a chaotic circuit with a single bipolar junction transistor (BJT) was described and analyzed, as an externally driven and controlled chaotic signal generator [1,2]. The operation of this circuit - characterized as a RLT circuit – was simulated using MultiSim, a widely accepted circuit simulation software that provides an interface adequately close to real implementation [3,4]. As a follow-up to this work, this paper examines the influence of a number of first and second order near neighbors in predicting chaotic time series using back propagation neural network.

2. Single Transistor Ciruit Description

The RLT circuit shown in Fig.1 (a). It consists of a basic common emitter configuration of a BC107BP npn-type BJT with an emitter degeneration resistor R_1=3KΩ and a collector resistor R_2=30Ω in series. The circuit is driven by an input sinusoidal voltage of amplitude V_1 applied through an inductor L=75μH directly to the transistor base where its power is supplied by a sinusoidal voltage υ_2 of amplitude V_2 connected to the transistor collector through R_2. We are examining its operation by means of the MultiSim circuit simulation environment, as illustrated in Fig.1(b), and by monitoring voltage υ_y across the emitter resistor R_1 and voltage υ_x across the collector resistor R_2.



(a)



(b)

Fig.1. (a) The considered RLT circuit, and (b) its simulation environment.

Clearly, both voltages υ_x and υ_y depend on the collector current i_C(t) which, under certain conditions, turns to be an important circuit parameter, since it will become chaotic when the circuit exhibits chaotic operation. For example, the initial RLT circuit in [1] exhibits chaotic operation although triggered by a sinusoidal (and definitely not chaotic) input voltage. This chaotic operation has been explained by the chaotic nature of the collector current as a result of the biasing state of both base-emitter and collector-base junctions that could have lead the transistor to operate in its reverse active region, [1]. Following that and considering the incorporated RLT circuit as shown in Fig.1, it is reasonable to expect that both the amplitude and frequency values of input signal υ_1=V_1sinω_1t as well as the supply voltage

* E-mail address: lmhanias@teihal.gr

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$\upsilon_2 = V_2 \sin\omega_2 t$, may strongly affect its operation and, most probably, the presence of chaos. This can be seen in Fig.2, which depicts the obtained chaotic time series of the output signal $\upsilon_y(t)=i_C(t)R_1$ for input signal amplitude V_1=13 volts and frequency f_1=1KHz and V_2=12 volts and frequency f_2=995 Hz.

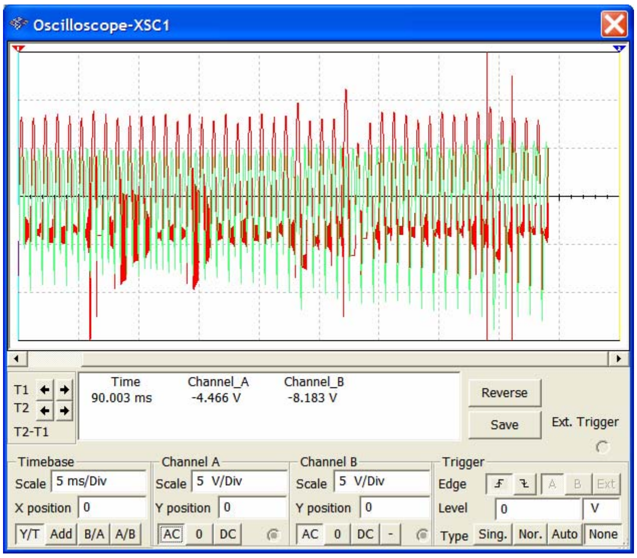

Fig.2. Chaotic output signal $\upsilon_y=\upsilon_y(t)$ (red – line) across the emitter resistor R_1 and $\upsilon_x=\upsilon_x(t)$ (green – line) across the collector resistor R_2 for the RLT circuit of Fig.1 (b). For f_1=1KHz and f_2=995Hz both time-series are chaotic.

3. RLT's strange attractor's properties

In order to examine the influence of a number of first and second order near neighbors in predicting chaotic time series we ought to find the corresponding numbers. From the previous work [2] it is known that the embedding dimensions of the emitter's and collector's voltage time series corresponding strange attractors, are 3 . For the emitter's voltage phase space and according to [2] ,we used embedding dimension m=3 and delay time, τ=13. Putting Theiler window at W=24 and applying the method proposed by [5, 6] we found:

for radius $\varepsilon = 1.81\mathrm{x}10^{-1}$, the number of first order Nearest Neighbors is found to be 6

for radius $\varepsilon=2.57\mathrm{x}10^{-1}$ the number of second order Nearest Neighbors is found to be 17

Also for the collector voltage's phase space we used embedding dimension m=3, delay time, τ=3, Theiler window W=26 and applying the same method we found:

for distance $\varepsilon = 1.98\mathrm{x}10^{-2}$, the number of first order Nearest Neighbors is found to be 10

for distance $\varepsilon=7.91\mathrm{x}10^{-2}$ the number of second order Nearest Neighbors is found to be 20.

4. Neural Network construction.

The next step is to forecast the time series. For this purpose we are going to construct a back propagation network with one hidden layer [7-9]. The number of inputs was equal to the embedding dimension while the number of neurons at hidden layer was equal to the number of first order and second order near neighbors correspondingly, while the transfer function was *tanh*. The efficiency of the network was measured by applying Mean Square Error between actual and forecasted values. For learning and testing purpose we used 70% percent of our data while the other 30% was used for "out of samples" forecasting. In all cases the learning process stopped at 100000 epochs with a learning rate equal to 0.1.

5. Time series prediction

For RLT time series we used as input from the multivariate time series the collector's time series and as output the emitter time series. The results of emitter voltage prediction are shown in Tables -1,2,3,4,5,6 and figures -4,5,6,7,8,9,

Table -1

	Input layer	1 hidden layer	Output layer	MSE
Number of neurons	3	6	1	0.000729545

Table -1. Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of first order Nearest Neighbors of emitter. The forecasting horizon was 1 time ahead.

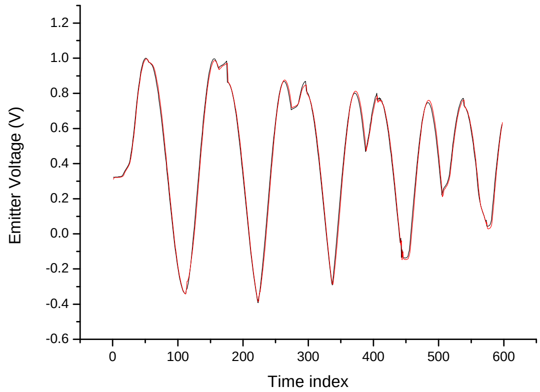

Fig -4 Actual (black line) and predicted (red – line) out of sample values of output chaotic signal across emitter (Parameters at Table -1)

Table -2

	Input layer	1 hidden layer	Output layer	MSE
Number of neurons	3	17	1	0.000738074

Table -2 Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of second order Nearest Neighbors of emitter. The forecasting horizon was 1 step ahead.

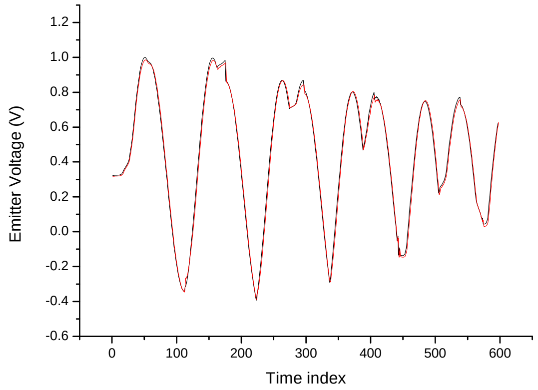

Fig -5 Actual (black line) and predicted (red – line) out of sample values of output chaotic signal across emitter (Parameters at Table -2)

Table -3

	Input layer	1 hidden layer	Output layer	MSE
Number of neurons	3	6	5	0.017719191

Table -3 Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of first order Nearest Neighbors of emitter. The forecasting horizon was 5 steps ahead.

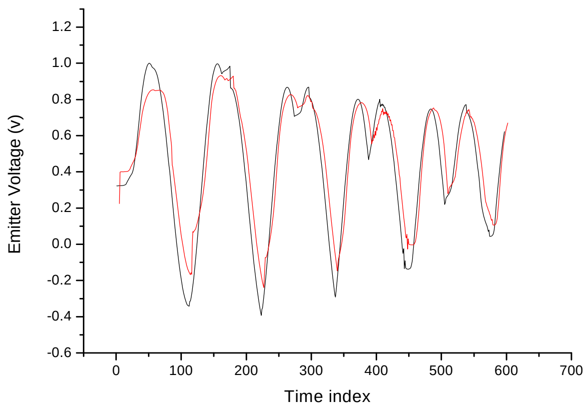

Fig -6 Actual (black line) and predicted (red – line) out of sample values ofoutput chaotic signal across emitter (Parameters at Table -3)

Table -4

	Input layer	1 hidden layer	Output layer	MSE
No of neurons	3	17	5	0.016408674

Table -4 Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of second order Nearest Neighbors of emitter. The forecasting horizon was 5 ahead.

It's clear that the MSE is smaller when we use the emitter's strange attractor's second order number of near neighbors compared to the first order number of near neighbors.

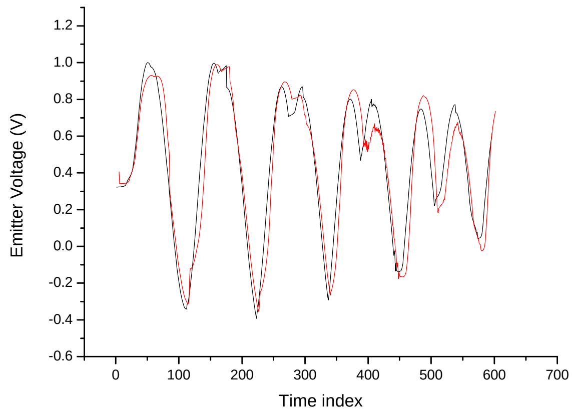

Fig -7: Actual (black line) and predicted (red – line) out of sample values ofoutput chaotic signal across emitter (Parameters at Table -4)

Table -5

	Input layer	1 hidden layer	Output layer	MSE
No of neurons	3	10	5	0.017483843

Table -5 Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of first order Nearest Neighbors of collector. The forecasting horizon was 5 steps ahead.

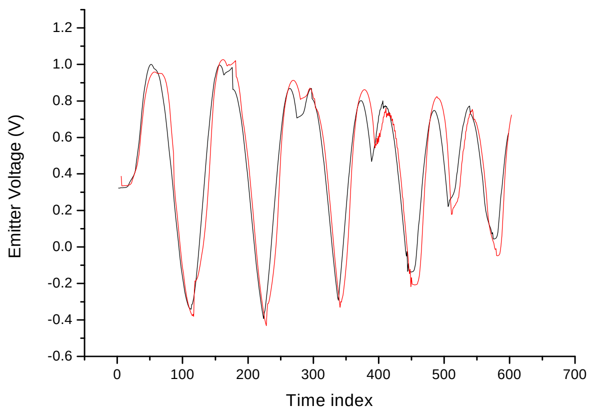

Fig -8:Actual (black line) and predicted (red – line) out of sample values ofoutput chaotic signal across emitter (Parameters at Table -5)

Table -6

	Input layer	1 hidden layer	Output layer	MSE
No of neurons	3	20	5	0.014810729

Table -6 Neural network parameters for forecasting emitter time series. The number of neurons at hidden layer is equal to the number of second order Nearest Neighbors of collector. The forecasting horizon was 5 steps ahead.

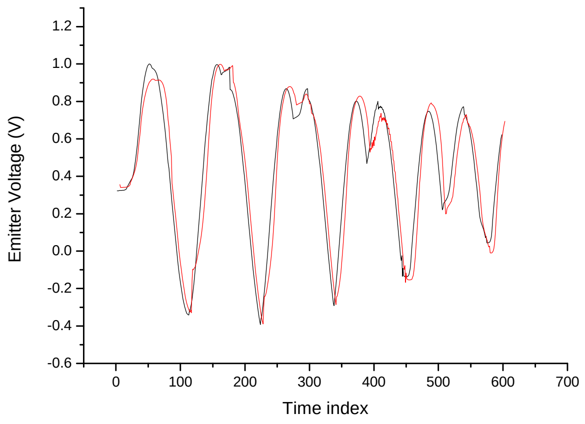

Fig -9:Actual (black line) and predicted (red – line) out of sample values ofoutput chaotic signal across emitter (Parameters at Table -6)

When we use the collector's strange attractor's second order number of near neighbors we get same results, i.e. the MSE is smaller when we use the second order number of near neighbors compared to the first order number of near neighbors.

6. Conclusion

From the above mentioned tables and corresponding figures it is clear that the quality of prediction depends on the number of near neighbors that was used as the number of hidden layer's neurons. According to MSE, the second order number of near neighbors gives smaller MSE than first order, particularly when the forecast horizon is increased. Conseycouently, using the emitter's strange attractor second order number of near neighbors we have better results compared to those when using the collector's strange attractor's second order number of near neighbors. This conclusion can be explained by assuming a chaotic nature of the collector current as a result of the biasing state of both base-emitter and collector-base junctions which could have lead the transistor to operate in its reverse active region.

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