Financial versus human Resources in the Greek - Turkish Arms Race 10 Years on: A forecasting Investigation using Artificial Neural Networks

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ABSTRACT

This paper looks into the Greek – Turkish arms race a decade after an earlier contribution on the issue that relied heavily on Artificial Neural Networks. The time period between the two papers contributes to the reliability of the results derived, not just by increasing the number of observations, but mainly by incorporating the progress made in the realm of Artificial Intelligence. The focus on the case of both counties unlike the paper mentioned above which dealt with just the Greek side provides ample room for comparative purposes regarding the determinants of defence spending on both sides. The results derived in terms of input significance estimation support the findings of earlier research as indicated above, pointing to the leading role of the demographic preponderance of Turkey over Greece. The paper also points to the fact that ten years later, Turkey continues to set the arms race rules against its rival by determining the defence expenditure of Greece while the role of the latter in affecting the military spending of Turkey is non-existent.

JEL codes: C45, H56

Keywords: Greece, Turkey, Arms Race, Neural Networks.

I. INTRODUCTION

The study of the arms race between Greece and Turkey has been the scope of Andreou and Zombanakis (2000). Going through the literature since then, it seems that this paper has contributed not only to outlining the arms race environment between the two countries, but also to explaining, to a large extent, the reasons why conventional analytical methods can not conclude as to the extent to which such a race is indeed going on (Andreou and Zombanakis, 2006). What we attempt to do now is to assess whether the conflict environment outlined ten years ago has remained the same thus adding to the burden of the two economies involved in it. We shall demonstrate, moreover, that the predominance of human over property resources is still one of the basic features in this arms race, in which Turkey determines, to the largest extent, the military spending of its adversary. We shall finally insist on employing Artificial Neural Networks which has been shown to be more efficient compared to conventional techniques "like regression analysis, time series decomposition, moving averages and smoothing methods, the Box – Jenkins methodology and numerous judgemental methods" as pointed out in Kuo and Reitsch (1995, p. 20).

II. LITERATURE UPDATE

Given that the literature background until the year 2000 has been dealt with in Andreou and Zombanakis (2000), we shall focus on papers since the beginning of the current decade when Brauer (2002 and 2003) provided an extensive analysis of a variety of issues referring to the broader Defence Economics literature on Greece and Turkey. Focusing on the specific arms race issue after the year 2000, there are five sources that treat the Greek – Turkish arms race issue in the context of a model. More specifically, Smith et al. (2000 II) consider the possibility of an arms race between the two sides using an econometric model and, alternatively, in the context of a two by two, Prisoner's Dilemma game, tracing little evidence of a traditional arms race appearing as an action–reaction process. What they trace, instead, is policy inertia, which emphasizes on bureaucratic and political criteria. Turning to Öcal (2002) the paper uses Smooth Transition Regression to trace considerable non- – linearities in a system that underlines an asymmetric behaviour indicating that "Greece does not want to fall behind Turkey" as it concerns defence expenditure. Athanassiou and Kollias (2002) and

Kollias and Sirakoulis (2002), tackle the effects of this issue rather than the issue itself, on foreign trade and arms imports respectively. Kollias and Paleologou (2002) seem to have reached a more straightforward conclusion based on the causality methodology developed by Hendry and Ericsson (1991) to trace bi-directional causality that reveals an arms race between Greece and Turkey. Andreou et al. (2002), employs an optimal control algorithm to estimate the optimal defence expenditure for Greece and Cyprus in the context of an arms race against Turkey. Brauer (2002) concludes that the arms race between Greece and Turkey must have ended sometime about mid-eighties, a conclusion that has been strongly challenged by Andreou and Zombanakis (2006) on the ground of a failure to reflect the actual political and strategic environment in the area.

Efforts to the direction of incorporating the influence of political and external security determinants[1] on the Greek demand for defence spending are made by Kollias and Paleologou (2003), which, however, has no choice but to adhere to the traditional solution provided by an extensive use of dummy variables while the use of dummy variables to improve the performance of Richardson – type models has been also tried by Dunne et al. (2005), encountering, however, a certain number of specification problems. Finally, Sahin and Ozsoy (2008) have chosen to employ a Markov switching approach in an effort to provide an empirical evaluation of the defence expenditure of Greece and Turkey.

III. TECHNICAL BACKGROUND

This section provides a very brief summary of the basic notions behind the main computational elements of the paper, namely Artificial Neural Networks (ANN). ANN may be viewed as directed graphs, composed of a number of basic computational elements called neurons or nodes and connections (weights or synapses) between them, forming layers. McCulloch and Pitts provided a model of a neuron similar to the biological neuron in the human brain. A Single-Layer Perceptron model following the principles suggested by McCulloch-Pitts consists of a set of inputs weights, a threshold and a hard limiter. ANN with neurons organised in multiple layers form the widely known Multi-Layer Perceptron (MLP) (McCulloch and Pitts, 1943) which is the basic prediction model in this paper In a feed-forward network, the units are partitioned into layers, with links from each unit in the k^{th} layer being directed to each unit in the $(k+1)^{th}$ layer. An *m*-*d*-1 architecture is shown in Figure 1, which refers to a network with *m* inputs, *d* units in the hidden layer and one output.

ANN of the *m*-*d*-1 architecture are trained over a number of examples so as to learn and then predict the behavior of the data series. The hidden and output layers realize a non-linear transfer function of the form:

$$f(y)=(1+\exp(-by))^{-1} \tag{1}$$

$$y=\sum_{i=1}^{n} w_i x_i \tag{2}$$

where x_i denote the input values of a node, while w_i the weights of edges connecting a node with *n* other nodes in the previous layer and *b* is the steepness of equation (1).

POSITION OF FIGURE 1

Figure 1 shows, in addition, a special node at the end of the input layer called "bias". This node has a fixed input value of 1 and feeds into all the neurons in the hidden and the output layers, with adjustable weights as the other nodes. Its role is to represent the adjustable neuron threshold levels explicitly in the transfer function input. The nodal representation eliminates the need to treat the threshold as a special neuron feature and leads to a more efficient algorithm implementation (Azoff, 1994).

The networks used in the present paper are Multiply Activated MLPs, which use one hidden layer partitioned into three parallel sub-layers activated by a different function (Figure 2).

POSITION OF FIGURE 2

Different topologies, as regards the number of nodes within the hidden layers, were implemented on a trial-and-error basis as regards forecasting accuracy. In addition, variations of learning schemes were adopted, lying on different activation functions, such as:

Logistic sigmoid : $$f(y)=(1+\exp(-by))^{-1} \quad (3)$$

Hyperbolic tangent : $$f(y)=(1-\exp(-by))*(1+\exp(-by))^{-1} \quad (4)$$

Gaussian : $$f(y)=\exp\left(-x^2\right) \quad (5)$$

Gaussian complement : $$f(y)=1-\exp\left(-x^2\right) \quad (6)$$

where, $$y=\sum_{i=1}^{n} w_i x_i \quad (7)$$

Given a time series x={x(t): $1 \leq t \leq N$} we form two sets, the training set xtrain={x(t): $1 \leq t \leq T$}, and the test set xtest={x(t): $T < t \leq N$}, where N is the length of the data series. The xtrain set is used to train the network until a certain level of convergence has been achieved based on some error criterion, while the xtest set is employed to test for overfitting.

The available data is organized in a set of patterns matching input to output sample values. These patterns are presented to a network during training with the goal being to characterise the relationship between inputs and outputs. During training of an MLP neural network, inputs of a training pattern propagate through the network, are multiplied by appropriate weights in the successive hidden layer(s) and the products are summed up. If the produced value exceeds a specified threshold, then the output of that node serves as input to another node in a subsequent layer. This process repeats until the network generates an output value for the corresponding input vector. The calculated output value is then compared to the desired output and an error value is determined for the particular input vector; the target here is to minimise the total error (i.e., the mean error of the set of input vectors) by modifying the weights of the connections between neurons. Processing continues, until a low error value is achieved, or training ceases to converge. After successful completion of training the network is tested against an independent set of vectors (i.e., data that did not participate in the training process) called the testing set. If the network is properly trained then it should be able to produce reasonably correct results against the test suite. MLP are usually trained in a supervised manner using the error back-propagation algorithm (Rumelhart and McLelland, 1986). The predicting behaviour of the MLP is characterised with the difference between the predicted and the desired output. The difference is propagated in a backward manner adjusting the necessary weights of the internal neurons, so that the predicted value is moved closer to the actual one. The advantages of using ANN include the ability to deal with domain complexity and generalise the knowledge gained, along with adaptability, flexibility and parallel processing (Haykin, 1999).

The number of iterations (epochs) presenting the whole pattern set during the learning phase was set to 2,000. One should be very cautious though when using a large number of epochs, as the network may overfit the data thus failing to generalize. Therefore the data overfitting problem was overcome by evaluating the performance of the ANN using the testing set, which includes portion of the dataset which is unseen, i.e. this set does not participate during the learning process (see e.g. Azoff, 1994). If the network has actually learned the structure of the input series rather than memorizing it then it can perform well when the testing set is presented. Otherwise, if bias or overfitting is really the case, performance will be extremely poor on these “new” data values.

The significance of the inputs feeding a successfully trained MLP may be calculated by summing the absolute values of the weights connecting the input layer to the first hidden layer, as explained in relevant studies (Refenes et. Al. 1995, Azoff, 1994).

One may argue that there are some limitation to the use of ANN. For example, MLP ANN trained with Backpropagational are “black boxes” in a sense. Apart from defining the general architecture of the ANN and its random initalisation, the user only feeds the inputs and receives the output. The final outcome of this process is in the best case a fully trained ANN that provides a fine mapping between inputs and outputs, but with no equations defining a relationship, as for example in OLS, other than that of the internal structure and mathematics of the ANN. The network itself is the actual equation defining the relationship. This, of course, is not a problem if the modelling attempt, as in our case, involves achieving a good input-output mapping of the available dataset, ruling out the possibility of overfitting as will be described later on, and not to produce a mathematical formula to describe the output(s) based on the inputs. Also, another known limitation with Backpropagation ANN is that they tend to be slower to train than other types of networks and sometimes require thousands of epochs. However, the speed of modern computers is such that this is typically not an issue.

IV. VARIABLE SPECIFICATION AND DESCRIPTION

The explanatory variables employed are reported in Table 1 together with the data sources. Each series ranges from 1961 to 2008, thus comprising 48 observations, out of which the training set includes 40 annual ones, up to and including the year 2000, while the testing set is composed of the rest 8 annual observations.

Among the variables included in Table 1, C and D representing respectively Greek and Turkish defence expenditure as a GDP share shall be the dependent ones while the rest shall be the explanatory variables determining C and D. Out of these A, P and Q (alternative to S) are taken to represent property resources while variables I, J, K, and L represent human resources. Finally, the nature of variables G and H is considered to mix both property and human characteristics.

Following the distinction between dependent and independent variables, the next step involves the estimation of input significance, that is, the identification of the inputs that essentially drive the learning process and promote the forecasting performance of the ANN model, which is essential in pointing to those variables with the highest explanatory power in an environment of an arms race between Greece and Turkey.

V. RESULTS

Table 2 includes a selection of the most plausible results with the network performance assessed on the basis of the Normalised Root Mean Square Error – NRMSE and the Mean Magnitude Relative Error – MMRE), together with the Correlation Coefficient (CC) calculated as follows:

$$\mathrm{NRMSE(n)} = \frac{\mathrm{RMSE(n)}}{\sigma_\Delta} = \frac{\mathrm{RMSE(n)}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x_{act}(i) - \overline{x}_{act,n}\right]^2}} \tag{8}$$

where,

$$\mathrm{RMSE(n)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x_{pred}(i) - x_{act}(i)\right]^2} \tag{9}$$

and

$$\mathrm{MMRE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_{pred}(i) - x_{act}(i)}{x_{act}(i)}\right| \tag{10}$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}\left[\left(x_{act}(i) - \overline{x}_{act,n}\right)\left(x_{pred}(i) - \overline{x}_{pred,n}\right)\right]}{\sqrt{\left[\sum_{i=1}^{n}\left(x_{act}(i) - \overline{x}_{act,n}\right)^2\right]\left[\sum_{i=1}^{n}\left(x_{pred}(i) - \overline{x}_{pred,n}\right)^2\right]}} \tag{11}$$

$x_{act}(i)$ and $x_{pred}(i)$ denote respectively the actual and the forecasted values of the variable in focus as provided by the network, $\overline{x}_{act,n}$, $\overline{x}_{pred,n}$ the average values of the actual and the forecasted sample of n observations respectively, with n standing for the total vector population.

The NRMSE is used to evaluate the quality of the forecasts derived comparing them with the corresponding forecasted values based on the simple mean of the last n values, while the MMRE, being a clear number, provides a percentage accuracy measure of the forecasts and focuses solely on the forecasted sample. Using this we are able to derive the forecast error in terms of percentage of the corresponding actual value a figure which makes the specific error measure more reliable compared to others. The correlation coefficient measures the extent to which the series forecasted by the network follows the fluctuations of the original series. It follows that a CC value close to unity denotes a coincidence of the actual and the forecasted series. A negative CC value shows that the forecasted series is a mirror image of the original one which means that if the latter displays an increasing trend then the trend of the former is symmetrically decreasing around the time axis and vice versa.

POSITION OF FIGURE 3 AND FIGURE 4

Table 2 and Figures 3 and 4 sum up the experiment results obtained using a multi-slab ANN model with 5 nodes in the first slab activated with the Gaussian function (eq. 5), 5 nodes in the second slab activated with the Hyberbolic Tangent function (eq. 4), 3 nodes in the third slab activated with the Gaussian Complement function (eq. 6), and 1 node in the output slab activated with the Logistic Sigmoid function (eq. 3), for both the training and the testing phase. The variables used to forecast the share of the Greek GDP devoted to defence expenditure are D, G, H, I, J, K, L, A and Q, while for the corresponding Turkish case the variables selected are C, G, H, I, J, K, L, and P. The performance of all networks has been very satisfactory with the MMRE of the best topology for the Greek case being of the order of 4,5%, against a considerably higher MMRE for the Turkish case, close to 13,5%.

The above have provided the background for the estimation of input significance which points to the leading determinants that predict the pattern of the Greek and Turkish defence expenditure as shown in Table 3.

The results are very much in line with the conclusions derived in Andreou and Zombanakis, (2000). We demonstrate, in other words, that the conclusions derived on the issue of the Greek – Turkish arms race ten years ago continue to outline the an environment of conflict between the two sides. More specifically, the main determinant of the Greek defence expenditure is the corresponding defence spending of Turkey, followed by the per capita expenditure for the armed forces of Turkey and finally the Greek per capita defence spending. In other words two out of the three top determinants of the Greek defence spending represent the Turkish side! It is most interesting to observe, however, that in the case of the Turkish defence expenditure all the leading determinants represent the side of Turkey, namely the armed forces per 1000 population, the per capita defence spending and the GDP rate of growth, in that order of importance. These findings, therefore, seem to be in line with similar research on the topic, like Kollias and Palaiologou (2002 and 2004), and confirm the conclusions derived by Andreou and Zombanakis (2000) according to which the initiative taken on the Turkish side determines the Greek defence expenditure. It is interesting to observe that there is no room to argue that the defence spending of Turkey would be seriously affected by any variable representing the Greek side. This shows that under the circumstances, Greece has no choice but to follow the Turkish defence expenditure pattern, a pattern clearly uniquely determined on the basis of Turkish criteria and interests. This means that Turkey retains the absolute initiative in the framework of the arms race against Greece with the latter simply being compelled to follow irrespective of the cost that such a race may entail. Thus one may observe that the growth rate of the Turkish GDP is one of the leading determinants of the country's defence spending which is not the case for Greece when it comes to its own GDP. This means that Greece has to decide on the course of its future defence expenditure irrespective of its economic performance whether this is described by the growth rate of the Greek GDP, the country's IIP, or its external debt. The second useful conclusion derived on the basis of the results obtained in this paper is the high explanatory power of the variables directly or indirectly related to human resources whereas those representing property resources make their presence felt only through the Turkish defence expenditure and the growth rate of the Turkish GDP interpreting developments of defence spending in Greece and Turkey respectively. This is a point which assumes considerable importance given the hopelessly low birth rate of Greece – which is not the case for Turkey – together with the extremely populist tactics followed by the Greek politicians concerning the reduction of the military service term.

Concluding this analysis we feel it may be interesting to assess the elasticity coefficients of defence expenditure in the two countries to changes in the main explanatory variables as these are included in Table 3. These elasticity coefficients have been calculated on the basis of OLS estimates as described in Table 4.

On the basis of these results it seems that defence expenditure is inelastic with regard to changes in the various explanatory variables, with the only point worth noting being the negative coefficient of the Turkish GDP when interpreting the defence spending of this particular country.

VI. CONCLUSIONS

The conclusions drawn in this paper are very much in line with the findings of several sources in the literature of this decade like e. g. Kollias and Palaiologou (2002 and 2004), as well as with those derived by Andreou and Zombanakis (2000).

Compared to the latter the findings of the present paper provide a bilateral picture by adding the Turkish side as well.

The conclusion that the pressure exercised on the Greek economy due to the arms race of the country against Turkey is not easy to mitigate remains one of the leading findings. In fact,

1. The predominance of the role of human over that of property resources continues to be a leading feature of this arms race.

2. The Turkish per capita defence expenditure comes to be the second important determinant of the Greek defence spending next to the military expenditure of Turkey which came to be the top determinant both ten years ago and in the present paper.

3. The paper adds to the research the complete absence of any variables reflecting the Greek side that can be considered as affecting the Turkish defence expenditure.

4. The combination of the predominance of Turkey in setting the arms race rules against Greece, together with the preponderance of human over property resources in this arms race, given the negligible birth rates in Greece, makes things even gloomier for the Greek side. On top of this the Greek authorities do not seem to realize the importance of the role of human resources in an environment of such an arms race resorting to populist measures like the reduction of the military service term which brings the defence readiness of the country into question.

In short the arms race environment which has initially been determined in the literature at the beginning of last decade has hardly changed compared to its present pattern, despite various policy recommendations and recipes for tension reduction proposed in the literature time and again (Brauer 2002 and 2003).

However, the nature of the arms race environment between Greece and Turkey offers plenty of room for additional research. For example, a multiple input - multiple output neural network structure would provide more insights into this controversial issue, given that an arms race is not just confined within the realms of defence expenditure, but in addition, it is related to the entire economic structure and performance of the two parties involved.

FOOTNOTES

[*] We are indebted to E. Petrou for data support and processing. We are also indebted to two anonymous referees for their constructive criticism.

[1] The basic features outlining the political and strategic background of the Greek – Turkish conflict are found in Andreou and Zombanakis (2006) along with a descriptive analysis of the underlying causes.

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TABLES

Table 1: Variables and Data Sources

Code Name	Time Series	Source
A	Greece: GDP Growth Rate	National Accounts
C	Greece: Defence Expenditure over GDP	NATO, SIPRI (Swedish International Peace Research Institute)
D	Turkey: Defence Expenditure over GDP	NATO, SIPRI
G	Greece: Per Capita Defence Expenditure	IISS (International Institute for Strategic Studies-London)
H	Turkey: Per Capita Defence Expenditure	IISS
I	Greece: Armed Forces per 1000 People	IISS
J	Turkey: Armed Forces per 1000 People	IISS
K	Greece: Population Rate of Growth	U. N. Population Statistics
L	Turkey Population Rate of Growth	U. N. Population Statistics
P	Turkey: GDP Growth Rate	IFS (International Financial Statistics – IMF)
Q (S)	Greece: General Government Total External Debt (Rate of Change)	Bank of Greece

Table 2 : Selected results using a multi-slab ann model with 5 nodes in the first slab (Gaussian activation), 5 nodes in the second slab (Hyperbolic Tangent activation), 3 nodes in the third slab (Gaussian Complement activation) and 1 node in the output slab (Logistic Sigmoid activation)

Case	Time Series	NRMSE	CC	MMRE
(A) Greek Defence Expenditure /GDP Determinants: D, G, H, I, J, K, L, A, Q	Training (1961 - 2000)	0.5213	0.8603	0.0947
	Testing (2001 - 2008)	0.5785	0.9264	0.0466
(B) Turkish Defence Expenditure /GDP Determinants: C, G, H, I, J, K, L, P	Training (1961 - 2000)	0.2450	0.9729	0.0384
	Testing (2001 - 2008)	0.7228	0.7232	0.1361

Table 3: Estimation of Input Significance for the System Determinants

Defence Expenditure	Main Determinants
Greece	1. Turkish Defence Expenditure / GDP 2. Turkish Per Capita Defence Expenditure 3. Greek Per Capita Defence Expenditure
Turkey	1. Turkish Armed Forces / 1000 Population 2. Turkish Per Capita Defence Expenditure 3. Turkish GDP Rate of Growth

Table 4 : Defence Expenditure Elasticities with Respect to Independent Variables Changes (t – Values in Parentheses)

Independent Variable	Greek Defence Expenditure / GDP	Turkish Defence Expenditure / GDP
Turkish Defence Expenditure / GDP	0,22 (2.43)	
Turkish Per Capita Defence Expenditure	-	0,64 (6.66)
Greek Per Capita Defence Expenditure	0,86 (10.52)	
Turkish Armed Forces / 1000 Population		0,43 (3.11)
Turkish GDP Growth Rate		- 0,04 (-4.68)

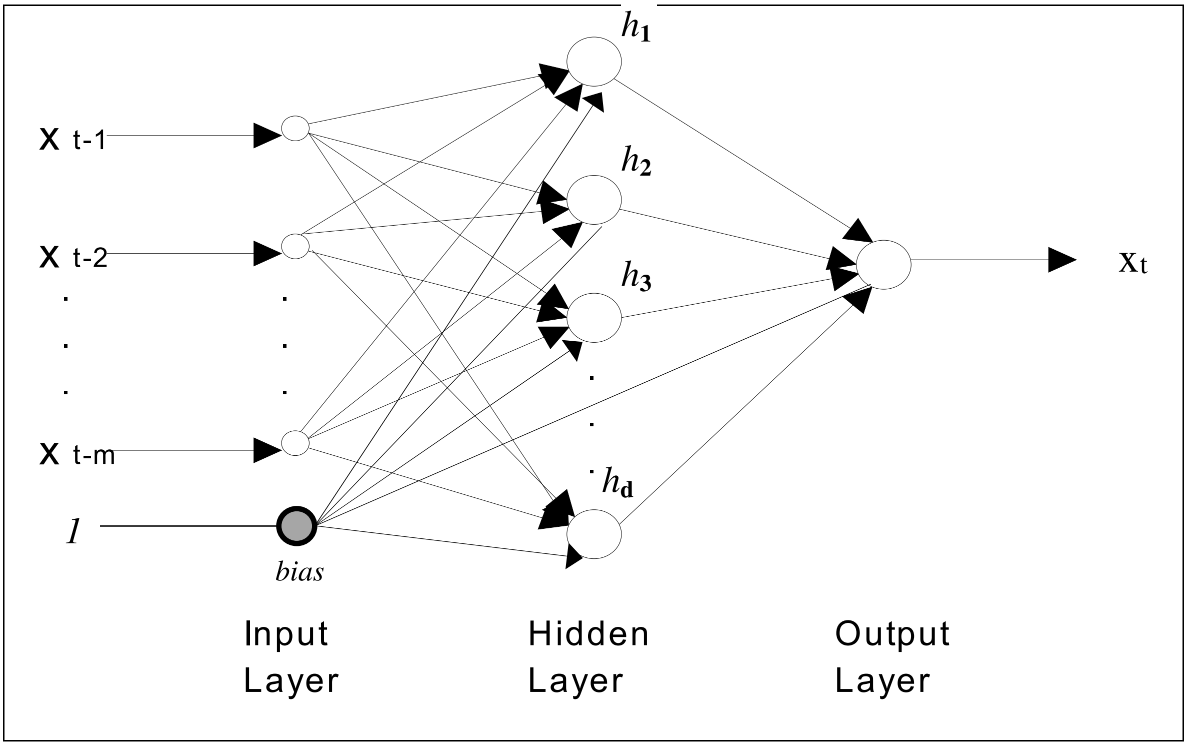
CAPTIONS FOR FIGURES

Figure 1. Graphical representation of a Multi-Layer Perceptron feed-forward neural network architecture, with m input nodes, one bias input, d hidden nodes and one output node

Figure 2: A Multiply Activated MLP Artificial Neural Network Architecture

Figure 3: Actual versus predicted values for the Greek Defence Expenditure/GDP using D, G, H, I, J, K, L, A as input variables a multi-slab ANN model with 5 nodes in the first slab (Gaussian activation), 5 nodes in the second slab (Hyperbolic Tangent activation), 3 nodes in the third slab (Gaussian Complement activation) and 1 node in the output slab (Logistic Sigmoid activation) (a) Training phase results, (b) Testing phase results

Figure 4: Actual versus predicted values for the Turkish Defence Expenditure /GDP using C, G, H, I, J, K, L, P as input variables in a multi-slab ANN model with 5 nodes in the first slab (Gaussian activation), 5 nodes in the second slab (Hyperbolic Tangent activation), 3 nodes in the third slab (Gaussian Complement activation) and 1 node in the output slab (Logistic Sigmoid activation) (a) Training phase results, (b) Testing phase results



h_1
h_2
h_3
h_d
X t-1
X t-2
X t-m
1
bias
x_t
Input Layer
Hidden Layer
Output Layer

Figure 1

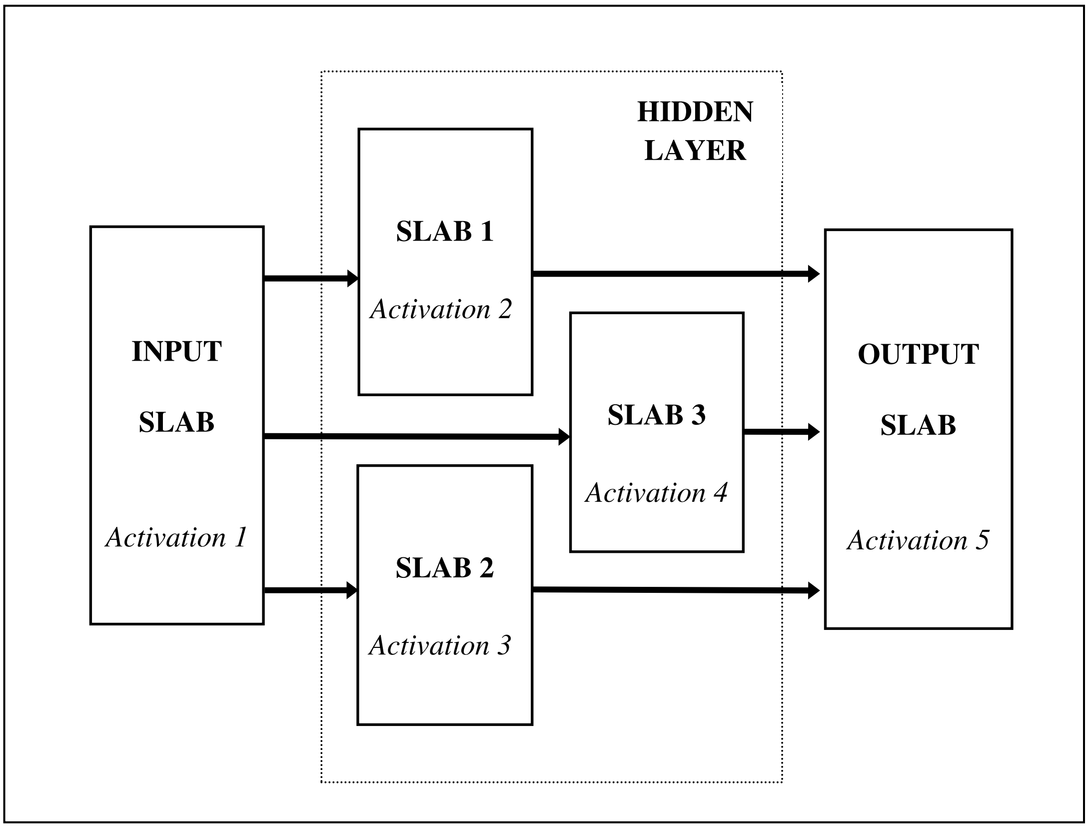
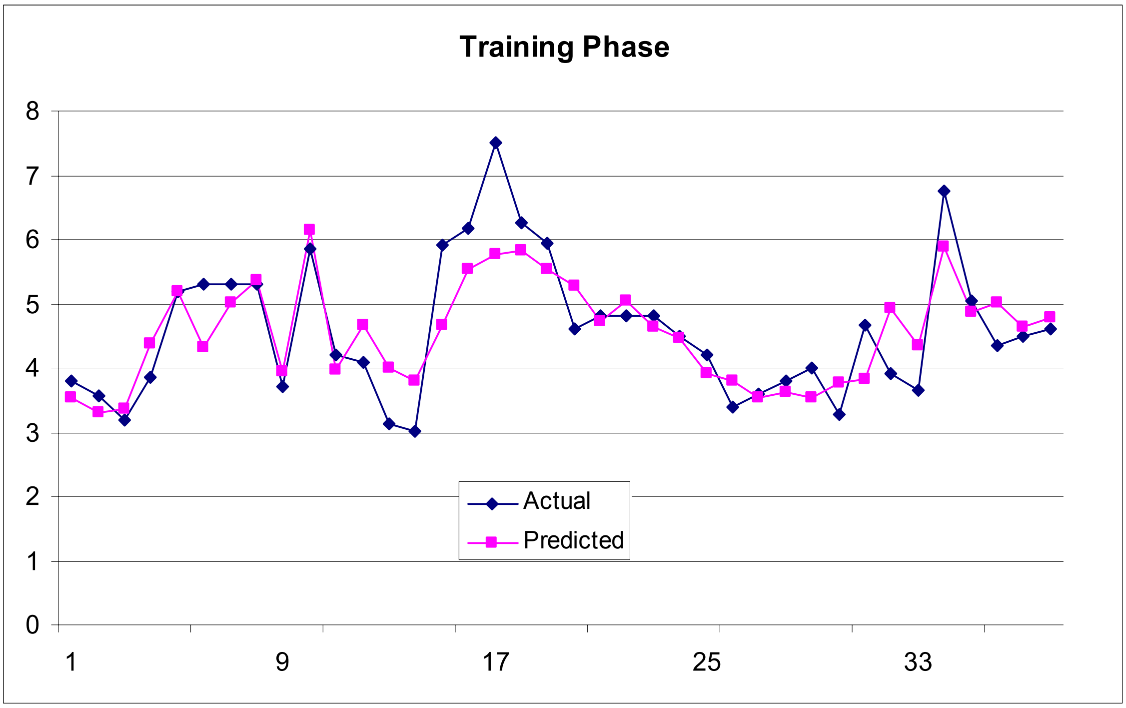
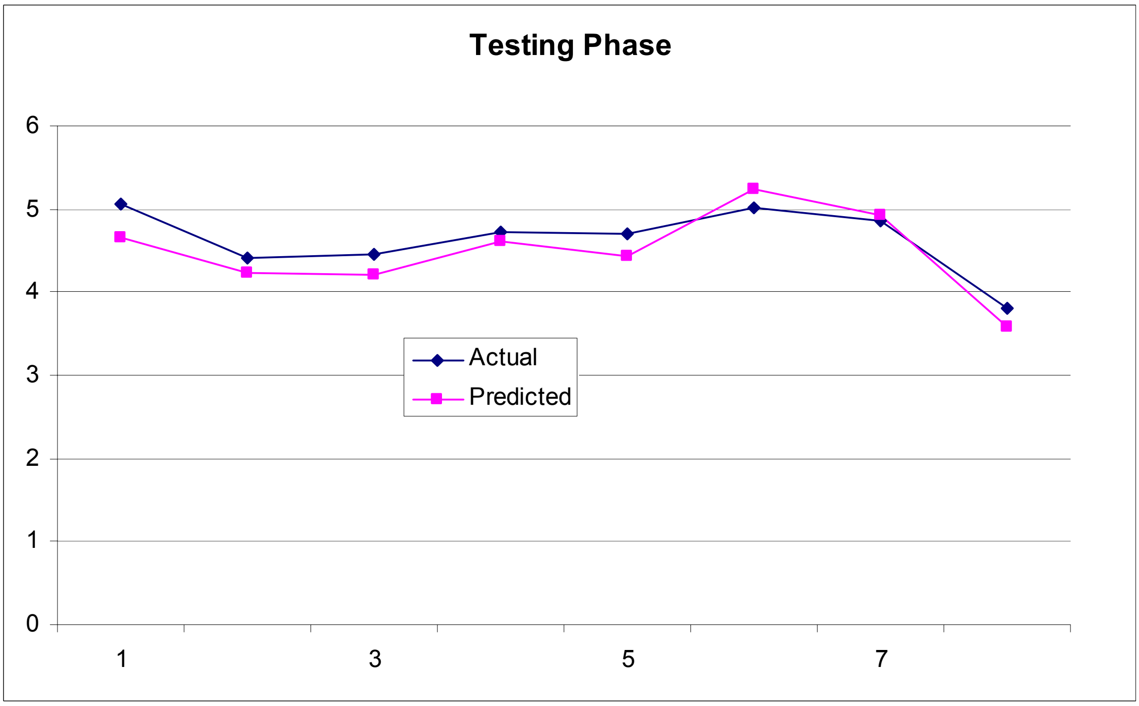

HIDDEN
LAYER
SLAB 1
Activation 2
INPUT
SLAB
Activation 1
SLAB 3
Activation 4
OUTPUT
SLAB
Activation 5
SLAB 2
Activation 3

Figure 2

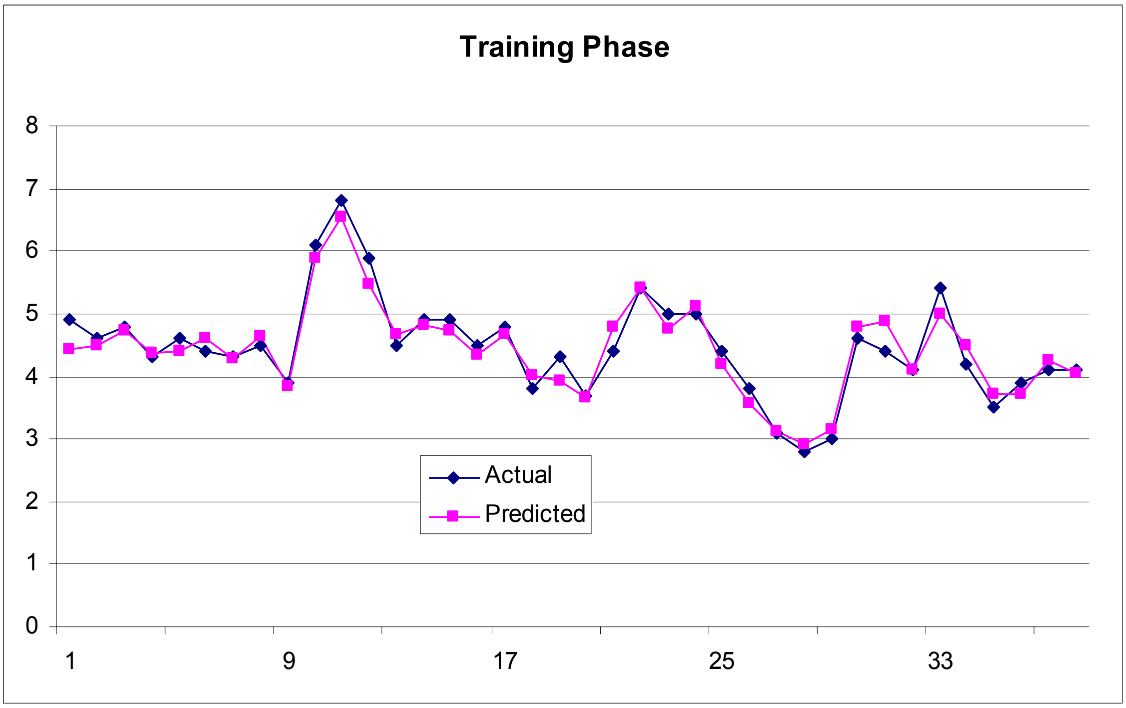

Training Phase
8
7
6
5
4
3
2
1
0
1
9
17
25
33
Actual
Predicted

(a)

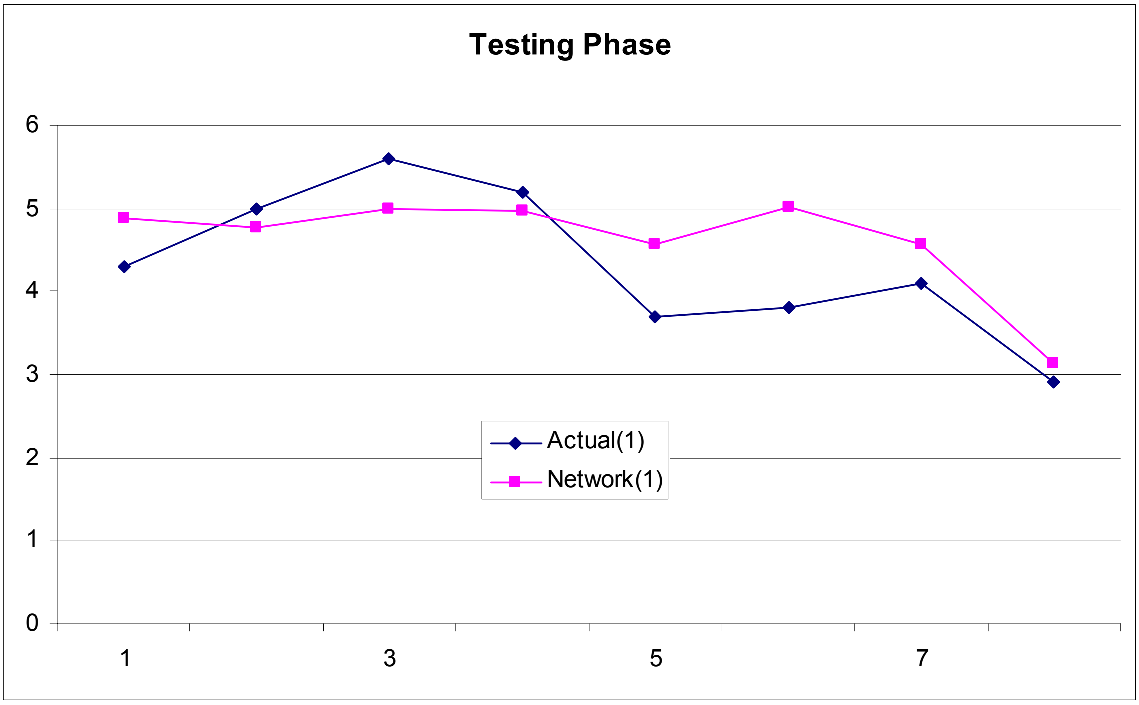

Testing Phase
6
5
4
3
2
1
0
1
3
5
7
Actual
Predicted

(b)

Figure 3


Training Phase
8
7
6
5
4
3
2
1
0
1
9
17
25
33
Actual
Predicted

(a)


Testing Phase
6
5
4
3
2
1
0
1
3
5
7
Actual(1)
Network(1)

(b)

Figure 4