A Neural Network Measurement of Relative Military Security: The Case of Greece and Cyprus

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Abstract

This paper aims at introducing a relative security measure, applicable to evaluating the impact of arms races on the military security of allies. This measure is based on demographic criteria, which play a dominant role in a number of arms races involving military alliances. The case of Greece and Cyprus, on one hand, and Turkey on the other, is the one to which our relative security measure is applied and tested. Artificial neural networks were trained to forecast the future behaviour of relative security. The high forecasting performance permitted the application of alternative scenarios for predicting the impact of the Greek - Turkish arms race on the relative security of the Greek - Cypriot alliance.

JEL codes: C45, H56

Keywords: Arms Race, Neural Networks, Relative Military Security

1. INTRODUCTION

The Greek - Cypriot Integrated Defence Space Doctrine has been regarded by the two parties involved as a strategy aiming at facing potential offensive action by Turkey against either of the two allies, with particular emphasis on the protection of their national interests in the Aegean Sea theatre. This paper does not aspire to criticise the effectiveness or otherwise of such a doctrine, since an attempt of this kind would touch upon sensitive issues requiring the use of classified information over and above the needs of scientific research. What one can certainly do, however, is attract the reader's attention to certain related issues, which may contribute to drawing a number of conclusions regarding the usefulness or otherwise of similar strategies, in view of the latest developments concerning the relations of the three countries involved.

These conclusions refer to the extent to which the security of the two allies in the area is promoted given the arms race which has long been going on between Greece and Turkey (Kollias and Makrydakis 1997). Whereas the impact of an arms race on the economy of the countries involved in it has been extensively dealt within the literature (Balfoussias and Stavrinos 1996; Ozmucur 1996; Kollias 1997), research referring to the consequences of arms races upon the security of the sides involved leaves a great deal to contribute on the issue. To forecast the impact of this arms race on the security of Greece and Cyprus we resort to using artificial neural networks, with all advantages a data driven approach may entail, given the complexity of the models employed by the theory of alliances and the contradictory empirical results (Hartley and Sandler 1995), as well as the limited theoretical background covering the concept of relative security in similar cases.

The technical support concerning the structure and training of the networks used is given in section 3, after the theoretical background, along with a description of the input variables and a brief review of the relevant literature have been presented in section 2. The forecasting results of the relative security factor, as well as a presentation and analysis of various alternative scenarios concerning arms race tactics between the countries involved are reported in section 4. Finally, section 5 sums up and concludes the findings of this paper.

2. LITERATURE OVERVIEW AND THEORETICAL BACKGROUND

The topic of arms races in its general context has been a rather popular issue, which was thoroughly investigated in the literature **(**e.g. Richardson 1960; Intriligator 1982; Isard and Anderton 1985 and 1988). Concerning the specific arms - race case between Greece and Turkey, earlier research has concluded that the pressure on the Greek economy resulting from this arms race is determined chiefly by demographic factors strongly favouring the Turkish side, while the estimation of input significance has indicated that the leading determinants of such a race describe the Turkish rather than the Greek economic and demographic environment (Andreou and Zombanakis 2000). Having established the above framework for the arms race between Greece and Turkey, we now proceed to investigate the extent to which its impact on the sides involved may be described by introducing a more specific and accurate measure compared to the hypothetical figures of a payoff matrix in the context of a game theory exercise (e.g. Wagner 1983). Such a measure requires defining a Relative Security (RS) coefficient, tailored to fit the environment of such a conflict involving Greece and Cyprus on one hand and Turkey on another. Ayanian (1994) has already employed such a security coefficient aiming at explaining exchange-rate fluctuations better than conventional macroeconomic variables. Combining Ayanian's reasoning on the subject together with our earlier conclusions regarding the leading role of population developments in the Greek - Turkish arms race, we have proceeded to determining an RS coefficient. This coefficient is suitable to use when measuring the impact of the Greek - Turkish arms race on the security of the two allies, namely Greece and Cyprus.

Following Ayanian (1994), we define the security of Greece and that of Cyprus in the context of an Integrated Defence Space Doctrine scenario as follows:

$$S_G = (1/ k) * [(F_G + F_C) / F_{TG}] \qquad (1)$$

and

$$S_C = (1/ k) * [(F_G + F_C) / F_{TC}] \qquad (2)$$

where S_G is the military security of Greece

S_C is the military security of Cyprus

F_G is total Greek defence forces

F_C is total Cypriot defence forces

F_{TG} is Turkish forces potentially directed against Greece

F_{TC} is Turkish forces potentially directed against Cyprus

k is the probability of a conflict between the sides involved

The measure of the relative security of Cyprus with reference to Greece RS_{CG}, which is the quintessence of the Integrated Defence Space Doctrine between Greece and Cyprus, is defined as the ratio of (2) over (1):

$$RS_{CG} = [F_{TG} / F_{TC}] \tag{3}$$

Turkish forces potentially directed against Greece and Cyprus can be considered as an increasing function of the relative population growth rates between Turkey on one hand and each of the two allies on the other. This specification is based on the conclusion drawn in the literature, as mentioned earlier on in this section, referring to the dominance of human resources over financial resources in determining the defence burden on the Greek economy as a result of the ongoing arms race with Turkey[1]. Thus, the corresponding relationships for the two allies, Greece and Cyprus, may be stated as follows:

$$F_{TG} = F_T\left[\exp\left(\dot{p}_G/\dot{p}_T\right)\right] \tag{4}$$

and

$$F_{TC} = F_T\left[\exp\left(\dot{p}_C/\dot{p}_T\right)\right] \tag{5}$$

where F_T stands for the total of Turkish armed forces and $\dot{p}_G$, $\dot{p}_C$, $\dot{p}_T$ denote the respective population growth rates for Greece, Cyprus and Turkey. The interpretation of (4) and (5) requires special attention due to the asymmetric effect of the variables involved: Thus, in a purely hypothetical case which would involve a faster growth of the

[1]Indeed, any variable which represents or includes developments in human resources in the countries involved may be suitable. Since, however, population developments are decisive in affecting most of the human resource variables, we feel that their role must be acknowledged as leading. The use of population growth rates rather than the corresponding levels aims at stressing the dynamic character of the relative security measure proposed.

Greek or Cypriot population compared to that of Turkey, one may argue that this difference in the population rates involved may be considered as representing a potential threat to Turkey, which would, therefore, be compelled to channel more forces to face those of the two allies[2]. However, where the Turkish population exhibits a faster rate of growth compared to that of Greece or Cyprus, which has always been the case, this will allow Turkey to increase F_T, which is the total Turkish forces, and provide for an increase of the forces facing Greece and Cyprus, thus offsetting the effect caused due to the reduction of the exponent.

Substituting the equivalent of F_{TG} and F_{TC} from (4) and (5) in (3) we come up with the following Relative Security (RS) measure between Greece and Cyprus:

$$RS_{CG} = \exp[x] \qquad (6)$$

$$\text{where} \qquad x = \left(\dot{p}_G - \dot{p}_C\right) \ / \ \dot{p}_T \qquad (7)$$

Equation (6) interpreted together with (7) show how the population rates of growth of the three countries involved are expected to affect the relative security of Cyprus with reference to Greece, as this is measured by RS_{CG}. More specifically, for an increase of this index as given by (6), x at time t_2 must be higher than x at an earlier period t_1 (t_1 and t_2 represent years in our case). In terms of (7), therefore, $x_1 < x_2$, or:

$$\left(\dot{p}_G(1) - \dot{p}_C(1)\right) \ / \ \dot{p}_T(1) \quad < \quad \left(\dot{p}_G(2) - \dot{p}_C(2)\right) \ / \ \dot{p}_T(2) \qquad (7a)$$

[2] Such extreme scenarios aim at just facilitating the interpretation of this relative security measure and must not be considered as reflecting reality by any means.

Bearing in mind that RS_{CG} as it is expressed by (6) and (7) measures the relative security of Cyprus, it is evident that (7a) holds true in the following three cases:

a. If $\dot{p}_T(1) > \dot{p}_T(2)$, holding $\dot{p}_G$ and $\dot{p}_C$ constant, as shown by equations (6) and (7).

b. If $\dot{p}_C(1) > \dot{p}_C(2)$, holding $\dot{p}_G$ and $\dot{p}_T$ constant, since F_{TC} in equation (5) will fall.

c. If $\dot{p}_G(1) < \dot{p}_G(2)$, holding $\dot{p}_C$ and $\dot{p}_T$ constant, since F_{TG} in equation (4) will rise, meaning that Turkish forces are expected to move towards Greece and away from Cyprus. This case underlines the importance of the Greek support in the Greek – Cypriot alliance, in the context of which, all population growth rates not included in one of the above cases entail a decline of the RS_{CG}, indicating a reduction of the relative security of Cyprus[3].

d. If all rates fluctuate, the direction of change of the RS will depend on the outcome of equation (7a), that is, RS will rise if the second term of (7a) is greater than the first.

It is now evident that this relative security measure can be used to provide for a much more precise strategy payoff measure compared to the hypothetical payoffs used in the literature, as we indicated earlier in this section. Indeed, if the percentage changes included in the exponent of (6) are instead denoted as logarithmic first differences, then the exponent x of the relative security measure RS_{CG} in (7) may be expressed as follows**:**

$$x = [\ \ln (P_G / P_G(-1)) - \ln (P_C / P_C(-1))\ ] / [\ \ln (P_T / P_T(-1))\ ] \qquad (8)$$

where P_G, P_C and P_T stand for the populations of Greece, Cyprus and Turkey respectively.

[3] We are thankful to an anonymous referee and to professor A. Bountis of the University of Patras, Greece, for their contribution to our analysis on this issue.

Denoting by g, c, and t the corresponding Greek, Cypriot and Turkish population increases, as given in (8) above, i.e:

$$g = \ln (P_G / P_G(-1)) \quad (9)$$

$$c = \ln (P_C / P_C(-1)) \quad (10)$$

$$t = \ln (P_T / P_T(-1)) \quad (11)$$

then, following Chiang (1984), x represents the algebraic solution of the following equation:

$$c * t^x - g = 0 \quad (12)$$

It is evident, therefore, that (12) provides the necessary theoretical framework within which a relative security coefficient may be developed and used to quantify the impact of the various strategies selected by the sides involved in an arms race.

The benefits of introducing such a measure and applying it using neural networks are clear:

a. It provides for a means to measure the impact of an arms race on the security of the allies involved in a much more specific way compared to the arbitrary payoffs found in the literature so far. Using, therefore, the relative security coefficient described in this paper, one may proceed to cardinal measurement comparisons among various arms race scenarios, thus drawing useful conclusions on the impact of such a race on the member states of an alliance.

b. This Relative Security coefficient, by emphasising the role of demographic variables, is tailored to fit the case of specific categories of arms races, in which human resources play a dominant role, such as the one between Greece and Turkey.

It is important to remember, however, that the application of this relative security coefficient is not necessarily confined to cases of two - member alliances. In fact, the number of the member countries in an alliance does not impose any constraint, as long as one focuses on the relative security involving pairs of member countries each time, facing a common threat.

The relative security coefficient for the Greek - Cypriot alliance thus established represents the output of our network algorithm, using as input some of the leading determinants of the Greek - Turkish arms race (Stavrinos and Zombanakis 1998; Andreou and Zombanakis 2000), as well as the top performing variables during preliminary input significance exercises (Table 1). The input variables thus selected are the GDP as well as its share representing defence expenditure of the three countries involved. In addition, the GDP share of the non - defence spending in Greece and Cyprus have been employed in order to introduce the opportunity cost of defence and thus the dimension of the peace dividend in the analysis.

3. TECHNICAL BACKGROUND

This section is devoted to present briefly the methodology of artificial neural networks. By using this data driven approach in forecasting the impact of the arms race on the security of the allies, one may avoid the complications arising due to the use of intricate models involving non-linearities, where, for example, the empirical results are occasionally contradictory. This approach is based on developing a “machine” composed of a number of basic computational elements called neurons, connected to each other forming layers. A network is trained through general-purpose algorithms based on available data. The problem is reduced to the computation of weight neuron connections in a feed-forward network to accomplish a desired input-output mapping. The learning phase can be viewed as a high dimensional, non-linear, system identification problem. In a feed-forward Multi-Layer Perceptron (MLP) links from each neuron in the k^{th} layer are being directed to each neuron in the $(k+1)^{th}$ layer. Inputs from the environment enter the first layer and outputs from the network are manifested at the last layer (Azoff 1994; Andreou and Zombanakis 2000).

The core architecture of our networks is the feed-forward MLP described above. Variations of this scheme were employed, such as the m-d-1 and m-d_1-d_2-1 topologies (m input nodes, one and two hidden layers respectively and one output) and a Multiply Activated (MA) one. The latter uses one hidden layer partitioned into three parallel sub-layers activated by a different function (Figure 1). All networks developed have one output neuron, which yields the next sample (predicted value) in the time sequence. The training algorithm used is the well-known Error Back Propagation with a momentum term (e.g. Rumelhart and McLelland 1986; Azoff 1994). The networks are trained to learn and then predict the behaviour of the time-series presented in specific patterns of data. Detailed information regarding architectural and learning parameters can be found in the Appendix (A.1).

The networks used in the present paper were divided into three categories: The first one employs MLPs with a single hidden layer (category A), the second one includes MLPs with two successive hidden layers (category B) and the last one involves the

Multiply Activated MLP (MAMLP – category C) described above. Different topologies, as regards the number of nodes within the hidden layers, were implemented. In addition, variations of learning schemes were adopted, lying on different activation functions (Table 2), such as:

$$\text{Logistic sigmoid :} \quad f(y) = (1 + \exp(-by))^{-1} \qquad (13)$$

$$\text{Hyperbolic tangent :} \quad f(y) = (1 - \exp(-by)) * (1 + \exp(-by))^{-1} \qquad (14)$$

$$\text{Gaussian :} \quad f(y) = \exp\left(-x^2\right) \qquad (15)$$

$$\text{Gaussian complement :} \quad f(y) = 1 - \exp\left(-x^2\right) \qquad (16)$$

$$\text{where,} \quad y = \sum_{i=1}^{n} w_i x_i \qquad (17)$$

and x_i*'s* denote the input values of a node, while w_i's the real valued weights of edges incident on a node and *n* the number of inputs to the node from the previous layer. *b* is known as the steepness of equations (13) and (14). The input layer is linear, while the output uses the sigmoid function.

Our data series consist of 33 annual observations, 25 of which were included in the training set and 8 in the testing set. The forecasting horizon was set to one step ahead. Performance was evaluated using well known and widely used error measures (see Appendix, A.2), specifically the Normalized Root Mean Squared Error (NRMSE), the Correlation Coefficient (CC), the Mean Relative Error (MRE), the Mean Absolute Error (MAE) and the Mean Square Error (MSE). All these measures were evaluated on the testing set of data, that is, a set of pattern values that did not participate during the course of learning.

An important aspect examined in the present analysis is the determination of the significance ordering of the variables involved, that is, the selection of the variables that contribute more to the forecasting process. This task can be performed using the notions of input sensitivity analysis, described extensively in Refenes et. al. (1995) and Azoff (1994), based on which one can sum up the absolute values of the weights fanning from each input variable into all nodes in the successive hidden layer, thus estimating the overall connection strength of this variable. The input variables that have the highest connection strength can then be considered as most significant, in the sense of affecting the course of forecasting in a more pronounced way compared to others. Presenting the analytical technical background behind these notions is beyond the scope of this work, since the reader may refer to the sources stated above for further information.

4. POLICY SIMULATIONS

The RS coefficient seems to be quite successful in predicting the impact on the relative security of Cyprus with reference to Greece, in the context of an arms race between the two allies on one hand and Turkey on the other, using the input variables described earlier. As indicated in Table 3, the error figures during the training phase reveal a very satisfactory performance. In general, performance after training was very successful as indicated by the Correlation Coefficient (CC), while the Normalised Root Mean Squared Error (NRMSE) indicates that predictions were by far better than the simple mean forecaster (NRMSE equal to 1). The deviation between actual and predicted samples, as indicated on the basis of the Mean Relative Error (MRE), the Mean Absolute Error (MAE) and the Mean Square Error (MSE) is negligible. As a result, the ability of the networks to generalise the knowledge embodied through the learning process during the testing phase is considerably high, as assessed on the basis of the corresponding errors for the out-of-sample data.

More specifically, the forecasting performance during the testing phase is quite successful in CC terms, which in certain networks, like C(2), C(3) and C(4) reached an approximate 84-89% follow up of the original series. Regarding prediction accuracy, the MSE, MRE and MAE error indicators exhibit low values in all networks, while the NRMSE figures indicate a slightly inferior behaviour compared to a simple mean predictor in most of the cases, with the exception of A(2) and all networks constituting the C category. The network that yields the most accurate predictions regarding all error measures used is C(2) (Figure 2), while the predictions of the rest C-category networks are also quite satisfactory. Finally, concerning the rest two network categories, only one network, namely A(2) presented a forecasting performance which can be considered as equally successful.

Before we move to examining how the relative security of the two allies may be affected in the context of alternative arms race scenarios, we turn to investigate the leading determinants of the relative security between Cyprus and Greece, facing the possibility of a Turkish threat. Input sensitivity analysis was performed for all networks used, following the learning phase, with the summation of weights corresponding to each input node (variable) presented in Table 4 in descending order. The findings of our experiments seem to be very much in line with earlier research on this topic (Andreou and Zombanakis 2000). Indeed, all experiments agree that the share of defence in the GDP of Turkey is clearly the top determinant of the Greek - Cypriot relative security. In most cases the Greek and Cypriot GDP shares of non - defence expenditure are the next two most important determinants of the relative security between the two allies. This finding underlines the importance of the trade - off between defence and non - defence spending and the extent to which the sacrifice of the peace dividend as a result of this specific arms race is too important to be overlooked, a conclusion which seems to agree with most of the literature (e.g. Hartley and Hooper 1990; Gleditsch et al. 1996).

Having identified the leading determinants of the relative security of the two allies with reference to Turkey, we may now proceed to study the simulation results of the networks forecasts of our relative security measure in the context of various arms race scenarios. The forecasting horizon included in the testing phase of the networks reaches the year 2002 and the results obtained confirm the findings of the literature on arms races and the various strategy payoffs (e.g. Wolfson 1985). The advantage of our method, however, lies with the possibility offered to substitute measurable payoffs for hypothetical, arbitrary values, thus obtaining a more meaningful cardinal measurement of the results of an arms race in the context of the Integrated Defence Space Doctrine. The scenarios selected are the usual ones involved in a typical arms race examined via game theory, or in the context of the “prisoner’s dilemma” (e.g. Majeski 1984). We assign, therefore, increasing or decreasing future values to the GDP shares of defence expenditure of Greece and Cyprus on one hand and Turkey on another[4], thus referring to the following four scenarios, with the terms “reduction” and “escalation” suggesting a respective decrease or increase of the GDP share of defence expenditure of the country or countries involved:

i. Both sides escalate.
ii. Greece and Cyprus escalate and Turkey reduces.
iii. Turkey escalates and Greece and Cyprus reduce.
iv. Both sides reduce.

Prediction of the future course of the RS coefficient in the context of the scenarios described above was performed using the C(2) network which achieved the highest forecasting performance during all earlier simulations.

As the prediction results in Table 5 indicate, RS behaves as expected, according to the theoretical basis stated earlier. The best outlook is provided in the case in which both sides choose to reduce tension by contracting their defence expenditure, as this is described by the GDP ratio of military expenditure, a finding to be expected bearing in mind the peace dividend for both sides as described in the literature (Balfousias and Stavrinos 1996; Ozmucur 1996). In this case, the Greece - Cyprus relative security coefficient RS for the five years forecasted assumes an average value of 4.82, the highest of all scenarios. The second best option, however, seems to be the case in which both sides resort to an arms race, this providing for an average 5 year RS forecasted value of 4.55.

[4] The choice of the defence expenditure as a share of the GDP rather than the level of the military expenditure itself is widely used in the literature and aims at introducing, to a certain extent at least, the question of sustainability of the defence burden by relating it to the total output of an economy.

The advocates of the “si vis pacem para bellum”[5] doctrine, however, will be delighted to observe that the year 2002 value of the RS coefficient in this scenario is practically equal to the corresponding value of the case in which both sides select the reduced defence spending policy. This finding is very interesting, since it underlines the importance of the arms race on the security of the alliance members. The cases in which one of the two parties emphasises military spending, while the other reduces, also appear to be very interesting. Indeed, the average RS value for the five - year period forecasted is 2.93 in the case in which Greece and Cyprus increase their GDP share of defence expenditure, while Turkey reduces it. This conclusion is very much in line with both the established theoretical framework (e.g. Hartley and Sandler 1995), as well as elementary reasoning, given that the RS reflects the relative security of the Greek - Cypriot side. It is also interesting to point out that the RS figures in all scenarios increase together with the time horizon, with the exception of those derived in the fourth scenario, namely the one in which Turkey escalates while Greece and Cyprus limit their defence expenditure. In this case the average of the RS figures, which decline with time up to 2002, does not exceed 0.4, a very low value for the security of the two allies, as expected. The graphical description of the results referring to all four scenaria as discussed above is shown in Figure 3.

5. CONCLUSIONS

The aim of this paper has been to contribute to the cardinal measurement of an arms race impact upon the security of two allies involved in such a race against a potential

[5] The Latin for “if you want peace prepare for war”

adversary. The analysis refers to the co-operation between Greece and Cyprus in the area of national security, something that has already been materialised in the context of the so-called Integrated Defence Space Doctrine. Our efforts have focused on supplementing the available literature on arms races by suggesting the introduction of a payoff relative security coefficient, emphasising the dominant role of human resources in this case and measuring the impact on the military security of the two allies as a result of an arms race against a third party, namely Turkey.

The main conclusion drawn after a variety of scenarios have been tried is that the short and medium term relative security of Cyprus and Greece is maximised when both sides involved in the arms race reduce their defence expenditures, while the arms race scenario appears as a second-best choice. When it comes to the long-run, however, it is interesting to see that the Greece-Cyprus relative security index assumes its maximum value in the context of an arms race between Greece and Cyprus on one hand and Turkey on the other. This finding supports the view of those who believe that despite the peace dividend (Balfousias and Stavrinos 1996), Greece has no choice but to follow up the ambitious 25-year Turkish armaments programme. Finally, the results of the “Turkey escalates-Cyprus and Greece reduce” scenario are discouraging due to their lowest relative security values and, consequently, their poor contribution to peace promotion, something that must be taken to consideration by the one - sided disarmament policy followers.

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TABLES

Table 1: Variables, Data and Sources

Code	Data Series	Source
GGDPCS	GDP of Greece, Constant Prices	Greek National Accounts
CGDPCS	GDP of Cyprus, Constant Prices	Cypriot National Accounts
TGDPCS	GDP of Turkey, Constant Prices	International Financial Statistics, IMF
GDEFCRS	Defence Expenditure of Greece (share of GDP)	SIPRI
CDEFCRS	Defence Expenditure of Cyprus (share of GDP)	SIPRI
TDEFCRS	Defence Expenditure of Turkey (share of GDP)	SIPRI
GNDEFCRS	Non-Defence Expenditure of Greece (share of GDP)	Greek National Accounts
CNDEFCRS	Non-Defence Expenditure of Cyprus (share of GDP)	Cypriot National Accounts

Table 2: Neural network architectures, activation functions and encoding.

Network Architecture*	Hidden Layer(s) Activation Function(s)	Code
8-10-1	Logistic sigmoid	A(1)
8-10-1	Hyberbolic tangent	A(2)
8-14-1	Logistic sigmoid	A(3)
8-14-1	Hyberbolic tangent	A(4)
8-10-5-1	Logistic sigmoid	B(1)
8-10-5-1	Hyberbolic tangent	B(2)
8-15-8-1	Logistic sigmoid	B(3)
8-15-8-1	Hyberbolic tangent	B(4)
8-3-3-3-1	1st slab: Gaussian, 2nd slab: Hyberbolic tangent; 3rd slab: Gaussian complementary	C(1)
8-3-3-3-1	1st slab: Gaussian, 2nd slab: Gaussian complementary; 3rd slab: Hyberbolic tangent	C(2)
8-3-5-8-1	1st slab: Gaussian, 2nd slab: Hyberbolic tangent; 3rd slab: Gaussian complementary	C(3)
8-3-5-8-1	1st slab: Gaussian, 2nd slab: Gaussian complementary; 3rd slab: Hyberbolic tangent	C(4)

* "m-d-n" stands for m input nodes, d nodes in the hidden layer and n output nodes.
"m-d-p-n" stands for m input nodes, d nodes in the first hidden layer, p nodes in the second hidden layer and n output nodes.
"m-d-p-k-n" stands for m input nodes, d hidden nodes in the first slab (total hidden neurons subset) of the hidden layer, p hidden nodes in the second slab, k hidden nodes in the third slab and n output nodes.

Table 3: Forecasting performance and error figures

Network	Training Phase					Testing Phase				
	NRMSE	MSE	CC	MRE	MAE	NRMSE	MSE	CC	MRE	MAE
A(1)	0.0613	0.00430	0.9980	0.0642	0.0445	1.0871	0.6909	0.7594	0.4779	0.4453
A(2)	0.0340	0.00130	0.9994	0.0393	0.0258	0.9425	0.5194	0.7526	0.5309	0.4613
A(3)	0.0644	0.00470	0.9978	0.0713	0.0479	1.0683	0.6672	0.7537	0.5006	0.4536
A(4)	0.0354	0.00140	0.9994	0.0372	0.0258	1.0518	0.6467	0.7589	0.4901	0.4523
B(1)	0.0619	0.00430	0.9980	0.0636	0.0426	1.1511	0.7746	0.7604	0.4908	0.4642
B(2)	0.0236	0.00120	0.9994	0.0332	0.0211	1.2462	0.9079	0.7598	0.5322	0.5282
B(3)	0.0738	0.00620	0.9972	0.0800	0.0592	1.1167	0.7290	0.7638	0.4305	0.4115
B(4)	0.0183	0.00030	0.9998	0.0176	0.0124	1.1554	0.7805	0.7588	0.5357	0.5151
C(1)	0.0113	0.00010	0.9999	0.0103	0.0066	0.7650	0.2264	0.8795	0.3689	0.2993
C(2)	**0.0070**	**0.00005**	**1.0000**	**0.0057**	**0.0041**	**0.6858**	**0.2183**	**0.8854**	**0.3338**	**0.2217**
C(3)	0.0037	0.00001	1.0000	0.0032	0.0025	0.8352	0.3683	0.8486	0.3806	0.4389
C(4)	0.0125	0.00010	0.9999	0.0095	0.0075	0.8511	0.2889	0.8367	0.3785	0.3199

Table 4: Input significance analysis (percentage in parentheses)

Neural Network	Input variables significance ordering (descending)							
	1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**
A(1)	TDEFCRS (24.12)	CGDPCS (16.76)	GNDEFCRS (14.08)	GDEFCRS (11.91)	GGDPCS (10.70)	CNDEFCRS (8.76)	TGDPCS (7.48)	CDEFCRS (6.20)
A(2)	TDEFCRS (21.65)	GNDEFCRS (17.69)	CGDPCS (14.49)	GDEFCRS (12.56)	CDEFCRS (11.40)	CNDEFCRS (8.75)	GGDPCS (8.33)	TGDPCS (5.13)
A(3)	TDEFCRS (22.21)	GNDEFCRS (17.49)	CGDPCS (15.84)	TGDPCS (10.03)	GDEFCRS (9.33)	CNDEFCRS (8.78)	GGDPCS (8.74)	CDEFCRS (7.58)
A(4)	TDEFCRS (23.11)	GNDEFCRS (16.37)	TGDPCS (11.52)	CGDPCS (11.51)	GGDPCS (10.51)	GDEFCRS (9.99)	CNDEFCRS (8.83)	CDEFCRS (8.17)
B(1)	TDEFCRS (25.43)	(CGDPCS (17.56)	GNDEFCRS (13.74)	GGDPCS (10.56)	CNDEFCRS (9.65)	GDEFCRS (9.22)	TGDPCS (8.09)	CDEFCRS (5.75)
B(2)	TDEFCRS (22.50)	GNDEFCRS (14.70)	CGDPCS (14.26)	GDEFCRS (12.24)	GGDPCS (9.96)	CNDEFCRS (9.25)	CDEFCRS (8.89)	TGDPCS (8.18)
B(3)	TDEFCRS (20.51)	CGDPCS (19.38)	GNDEFCRS (11.51)	GGDPCS (11.35)	GDEFCRS (10.60)	CNDEFCRS (9.58)	TGDPCS (9.37)	CDEFCRS (7.71)
B(4)	TDEFCRS (18.53)	GNDEFCRS (15.19)	GDEFCRS (13.32)	CGDPCS (12.56)	GGDPCS (12.50)	CNDEFCRS (11.35)	CDEFCRS (9.90)	TGDPCS (6.66)
C(1)	TDEFCRS (25.10)	GNDEFCRS (15.44)	GGDPCS (14.11)	GDEFCRS (13.18)	CNDEFCRS (9.87)	CGDPCS (8.98)	CDEFCRS (7.47)	TGDPCS (5.85)
C(2)	TDEFCRS (20.67)	GNDEFCRS (19.64)	CNDEFCRS (12.26)	CGDPCS (11.26)	GGDPCS (10.92)	GDEFCRS (10.89)	TGDPCS (8.20)	CDEFCRS (6.17)
C(3)	TDEFCRS (19.82)	GNDEFCRS (15.41)	CNDEFCRS (12.36)	CGDPCS (12.25)	GDEFCRS (11.71)	GGDPCS (10.13)	CDEFCRS (9.35)	TGDPCS (8.97)
C(4)	TDEFCRS (19.52)	GNDEFCRS (16.45)	CNDEFCRS (11.99)	GDEFCRS (11.68)	CGDPCS (11.51)	GGDPCS (10.35)	TGDPCS (10.23)	CDEFCRS (8.27)

Table 5: Case scenarios predictions on the Relative Security (RS) coefficient

Scenario	Year	Predicted RS
All countries escalate	1998	1.4469
	1999	2.4368
	2000	4.0670
	2001	6.1940
	2002	8.5902
Cyprus and Greece escalate, Turkey reduces	1998	1.6812
	1999	2.3682
	2000	2.9593
	2001	3.5439
	2002	4.1159
Turkey Escalates, Cyprus and Greece Reduce	1998	0.7649
	1999	0.6195
	2000	0.3689
	2001	0.1808
	2002	0.0675
All countries reduce	1998	1.6406
	1999	3.0701
	2000	4.6800
	2001	6.4924
	2002	8.2233

LEGENDS FOR FIGURES

Figure 1: The Multiply Activated Multi-Layer Perceptron (MAMLP) neural network architecture.

Figure 2: Actual versus predicted values of the Relative Security (RS) coefficient using an 8-3-3-3-1 MAMLP neural network architecture.

Figure 3: Predicted values of the Relative Security (RS) coefficient for hypothetical scenaria, using an 8-3-3-3-1 MAMLP neural network architecture.

FIGURES

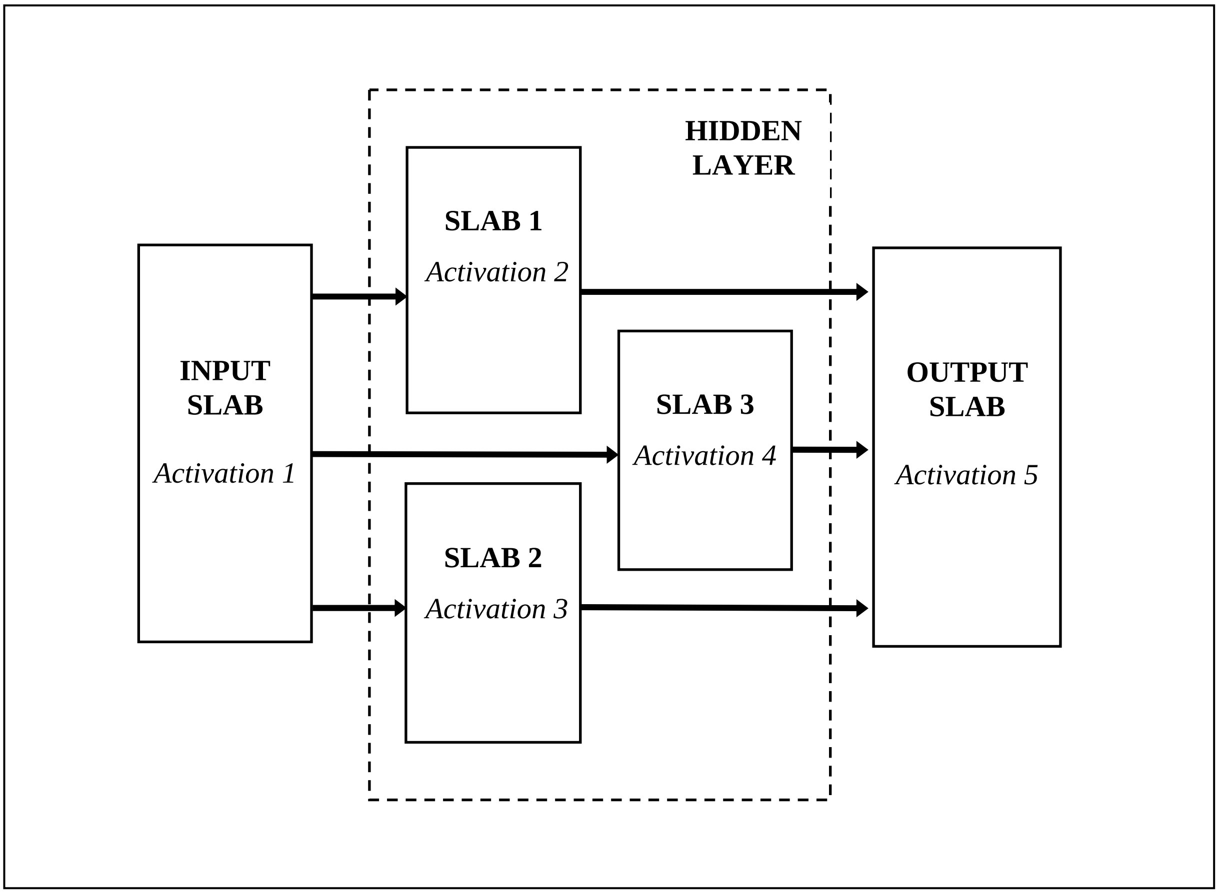


Figure 1

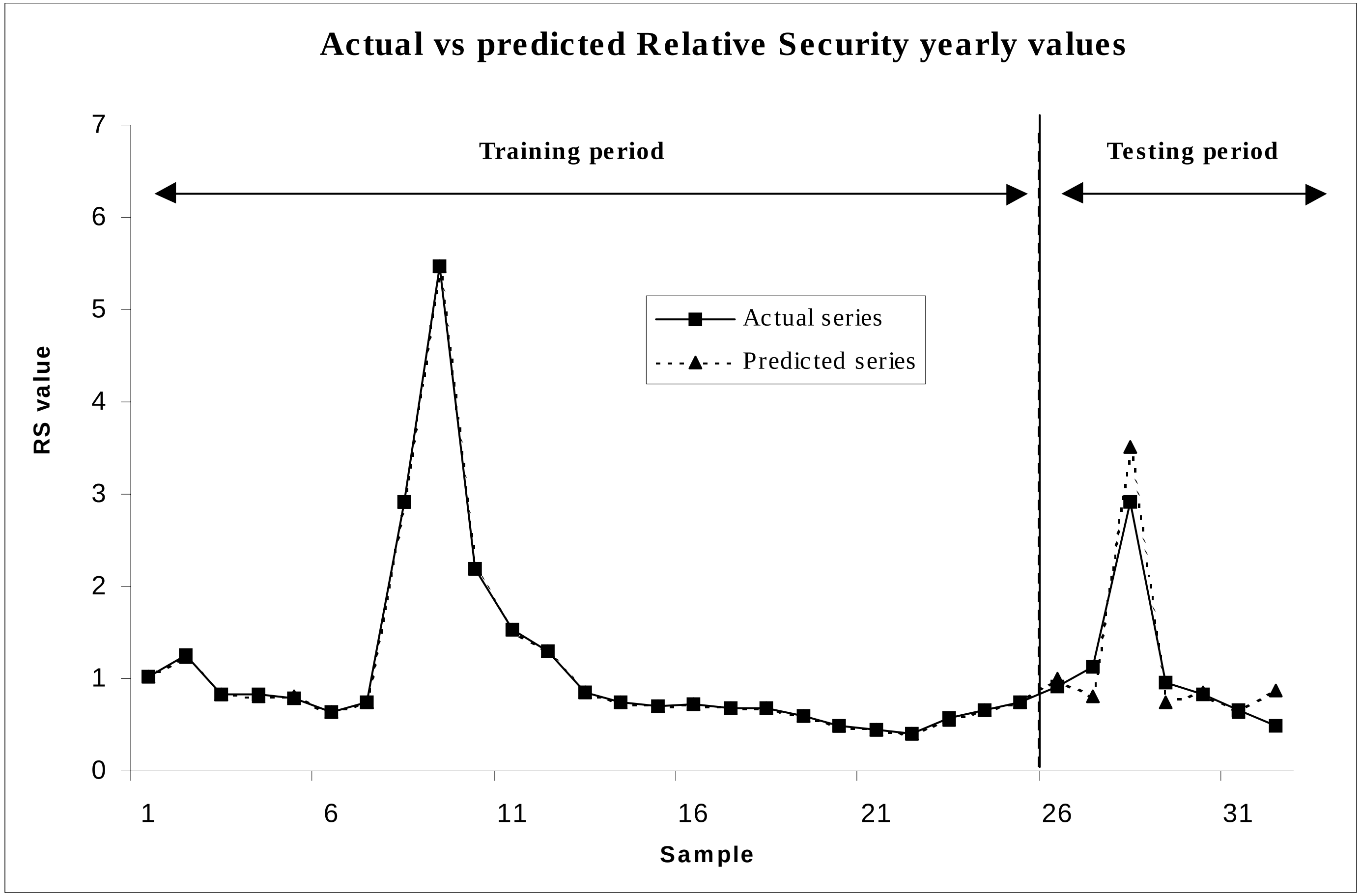
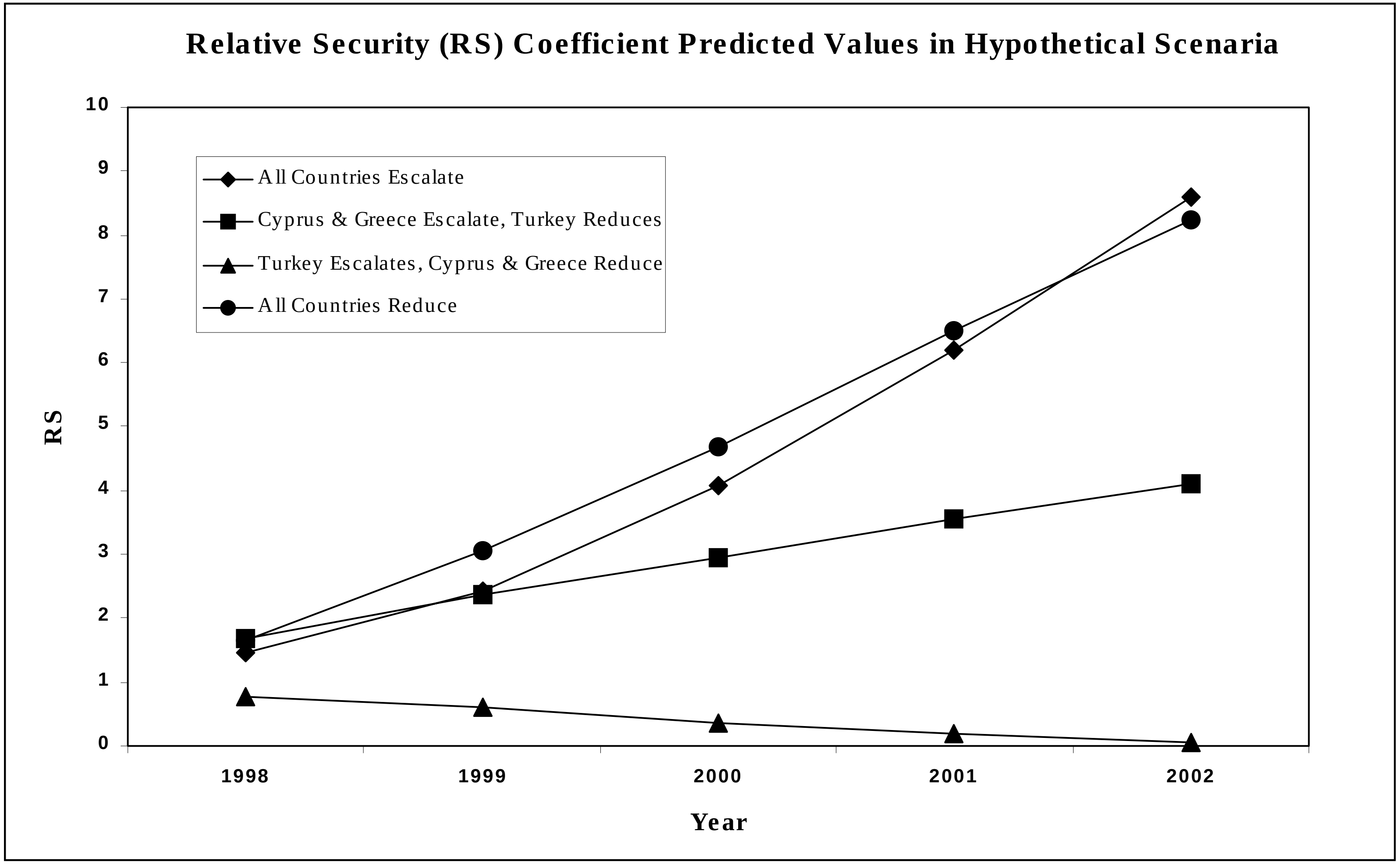

Actual vs predicted Relative Security yearly values
7
6
5
4
3
2
1
0
RS value
Training period
Testing period
Actual series
Predicted series
1
6
11
16
21
26
31
Sample

Figure 2



Relative Security (RS) Coefficient Predicted Values in Hypothetical Scenaria
All Countries Escalate
Cyprus & Greece Escalate, Turkey Reduces
Turkey Escalates, Cyprus & Greece Reduce
All Countries Reduce
RS
10
9
8
7
6
5
4
3
2
1
0
1998
1999
2000
2001
2002
Year

Figure 3

APPENDIX

A.1 System design and implementation

The given time series x={x(t): $1 \leq t \leq N$} is divided into two sets: a training set x_{train}={x(t): $1 \leq t \leq T$}, and a test set x_{test}={x(t): $T < t \leq N$}, where N is the length of the data series. The training phase presents the x_{train} set to the network repeatedly until a certain level of convergence is achieved based on some error criterion. The learning algorithm adjusts the weights in each repetition in order to minimize the diversion of the desired value from the predicted one.

The number of input neurons and the selection of the variables involved have been based on prior research on the topic, as stated in section 2, which has led to the choice of the input set which exhibits the highest performance in terms of prediction accuracy. We used several alternative configuration schemes, as regards the number of hidden layers and the nodes within each layer, in order, first to achieve best performance and second, to facilitate comparison between different network architectures (Table 2). Every input variable is associated with one neuron in the input layer.

Determining the number of hidden layers and neurons in each layer can often be a very difficult task and possibly one of the major factors influencing the performance of the network. Too few neurons in a hidden layer may produce bias due to the constraint of the function space, which results to poor performance as the network embodies a very small portion of information presented. Too many neurons on the other hand may cause overfitting of data on one hand and increase considerably the amount of computational time needed for the network to process data on the other, something that will not necessarily lead to convergence. We therefore have used a variety of numbers of neurons within one hidden layer, while in some cases a two-hidden-layer scheme was also developed in order to investigate whether performance is improved.

The number of iterations (epochs) presenting the whole pattern set during the learning phase is also very important. We have let this number vary during our simulations, since different network topologies, initial conditions and input sets, require different convergence and generalization times. The number of epochs our networks needed for convergence was 10,000, while the learning and momentum coefficients (Rumelhart and McLelland 1986; Azoff 1994) were kept constant at the positive values of 0.3 and 0.1 respectively. One should be very cautious though when using a large number of epochs, as the network may overfit the data thus failing to generalize. The problems of bias and data overfitting can be overcome by evaluating the performance of each network using a testing set of unseen patterns (testing phase). This set does not participate during the learning process (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. Architecture selection is generally based on success during the testing phase, provided that the learning ability was satisfactory.

A.2 Performance evaluation

The CC measures the ability of the predicted samples to follow the upward or downward jumps of the original series. A CC value near 1 in absolute terms is interpreted as a perfect follow up of the original series by the forecasted one. A negative CC sign indicates that the forecasting series follows the same ups or downs of the original series with a negative mirroring, that is with a 180^{o} rotation about the time-axis. When the original series moves up, the forecasting moves down at the same time-period and vice versa.

The NRMSE indicates whether prediction is better than a simple mean forecaster. If NRMSE=0 then predictions are perfect; NRMSE=1 indicates that prediction is no better than taking x_{pred} equal to the x-mean.

MRE shows the accuracy of predictions in percentage terms expressing it in a stricter way, since it focuses on the sample being predicted, not depending on the scale in which the data values are expressed or on the units of measurement used. Thus, we are able to estimate prediction error as a fraction of the actual value, this making the MRE the more objective error measure among the three used.

MSE is reported in order to have the error condition met by the Back Propagation algorithm, while the MAE shows the divergence between actual and predicted samples in absolute measures. The above prediction error measures are given by the following equations:

$$\mathrm{NRMSE}(n) = \frac{\mathrm{RMSE}(n)}{\sigma_{\Delta}} = \frac{\mathrm{RMSE}(n)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x_{act}(i) - \overline{x}_{act,n}\right]^{2}}} \qquad (18)$$

where,

$$\mathrm{RMSE}(n) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x_{pred}(i) - x_{act}(i)\right]^{2}} \qquad (19)$$

$$CC = \frac{\sum_{i=1}^{n}\left[\left(x_{act}(i)-\overline{x}_{act,n}\right)\left(x_{pred}(i)-\overline{x}_{pred,n}\right)\right]}{\sqrt{\left[\sum_{i=1}^{n}\left(x_{act}(i)-\overline{x}_{act,n}\right)^{2}\right]\left[\sum_{i=1}^{n}\left(x_{pred}(i)-\overline{x}_{pred,n}\right)^{2}\right]}} \quad (20)$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_{pred}(i)-x_{act}(i)}{x_{act}(i)}\right| \quad (21)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_{pred}(i)-x_{act}(i)\right| \quad (22)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_{pred}(i)-x_{act}(i))^{2} \quad (23)$$

where $x_{act}(i)$ and $x_{pred}(i)$ the actual and predicted value when pattern i is presented, $\overline{x}_{act,n}$, $\overline{x}_{pred,n}$ the mean value of actual and predicted samples of length n and n is the total number of patterns.