Return to Growth: Does it mean more on Defence Expenditure?

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Abstract. The Greek economy is expected to return to growth paths after a prolonged recession period. Our paper focuses on considering developments on the defence expenditures issue given that the majority of the procurement programmes have either been canceled or postponed following the "Troika" (the International Monetary Fund - IMF, the European Central Bank- ECB and the European Commission-EC) recommendations since the crisis started. The paper employs neural networks to assess the hierarchy ordering of the explanatory variables in the Greek demand for defence expenditures function relying on their explanatory power. It turns out that both property and human resources play a vital role in explaining defence spending developments in Greece. The results derived based on a forecasting investigation lead to a number of conclusions concerning the expected developments on the defence procurement policy to be followed, as well as on the determinants of such developments.

I. Introduction

The discussion regarding defence spending in Greece has grown to becoming a debate in the literature, approached in the light of mainly two perspectives, i. e. the country's questionable economic performance and the escalating demands from the part of Turkey to revise the status-quo in the Aegean and the Eastern Mediterranean. The fact remains, however, that during the recent economic crisis the European Commission (EC), the European Central Bank (ECB) and mainly the International Monetary Fund (IMF) have been insisting that defence procurement cuts must be a top priority[1]. This policy recommendation has been encouraged following the recent NATO summit, during which it has been pointed out that Greece is one of just five member countries that contribute 2% or more of their GDP to defence[2]. Bearing the above in mind and in view of the possibility that the outlook for Greece is

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[1] In fact the IMF has repeatedly in the past expressed its concerns on the issue of "excessive defence spending" (IMF, 2010, 2012 and 2014).

[2] This is a rather naïve approach concerning the issue of NATO members burden sharing, considering that in most cases about 70% of total defence spending reflects expenditure on personnel wages and salaries leaving only about 10 to 15% for equipment procurement.

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a return to a growth path the issue of providing some room for an increase in defence spending has become more than pressing. The urgency of the matter is justified since all procurement programmes of the Hellenic Armed Forces (EMPAE) have been cancelled or postponed during the crisis years thus endangering their effectiveness in a period during which Turkey raises increased claims in the area of the Aegean and Eastern Mediterranean.

In the light of this background we shall attempt to consider the extent to which the forecasted economic recovery of the Greek economy may offer some room for channeling more funds to defence expenditure and the reasons that justify such a defence spending increase. To do so we shall resort to using neural networks (ANNs), an option regarded as being more suitable for the purposes of the present analysis as explained later on in this paper. Thus, after a brief literature review we proceed to presenting and analyzing the input data and the methodology used in the analysis. Sections IV and V present the ANN results and the policy implications derived while the last section of the paper considers the conclusions drawn.

II. A Brief Literature Review

The majority of the papers on the issue use conventional models for a time series or panel analysis employing three main variable categories: Economics and production, technology and geopolitical and security ones. Following a number of early, well-established contributions in the literature like Smith (1980 and 1989), Hartley and Hooper (1990), Jones-Lee (1990), and Hewitt (1992), some focusing on developing countries e. g. (Deger and Smith 1983), Biswas and Ram, 1986), there has been a number of papers concentrating on individual country cases (Murdoch and Sandler 1985, Looney and Mehay 1990, Okamura 1991) or alliances (Murdoch and Sandler, 1982, Knorr,1985). The case of Greece occupies a leading position in the literature as it is involved in an arms race against Turkey (e. g**.** Sezgin, 2000, Andreou and Zombanakis 2000)[3]. Coming to recent contributions, there seems to be a trend which emphasizes on human resources and raises welfare considerations some of them with reference to the Chinese case like Ying Zhang, Rui Wang and Dongqi Yao (2017), Ying Zhang, Xiaoxing Liu, Jiaxin Xu and Rui Wang (2017) and Fumitaka et al. (2016). In fact, human resources variables like population growth and per capita income are considered as significant determinants (Dunne and Perlo-Freeman, 2003). Finally, on the techniques of analysis issue and following the inconclusive results derived on this issue using conventional models (Hartley and Sandler 1995, Taylor 1995, Brauer 2002) the focus has shifted towards artificial intelligence methods and specifically Artificial Neural Networks (ANN) to determine the defense expenditure of Greece (Andreou and Zombanakis 2006).

[3] It has now been established in the literature that the Greek side is compelled to follow the Turkish defence procurement policy regardless its direction of change and refers to earlier work on this issue (Andreou and Zombanakis 2006) in which an arms race between the two sides has been established despite occasional objections (Brauer 2002).The fact is, however, that the defence potential of Turkey has risen despite its recent economic problems, with the government aiming even at purchasing F-35 stealth fighters for $100 million each. By contrast, the ability of Greece to build up a reliable defence industrial base will be eroded in an environment of capital controls that outline an investment-hostile economy.

ANN belongs to a class of data driven approaches, as opposed to model driven approaches most frequently used in the analysis. Some of the advantages of using ANN as these have been analyzed in the literature (Kuo and Reitch, 1995, Hill et al. 1996) are the following: First, they do not require any a - priory specification of the relationship between the variables involved in the relationship under consideration. Thus, in cases of disagreement on the issue of the explanatory variables to be used or in cases in which there is lack of a strong theoretical background the ANN are considered to be preferable[4] Quoting Beck et al. (2004), neural networks "can approximate any functional form suggested by the data, even if not specified by one's theory ex ante". In other words, neural networks are particularly suitable for a large number of Defence-studies cases in which a standard theory cannot conclude as to a specific model structure or when immediate response to environment changes is required. In addition, in cases in which certain variables are correlated or exhibit a non-linear pattern of behaviour the ANN are more applicable. This is due to the fact that ANN, being a data-science model, are not affected by statistical multicollinearity issues while their non-linear nature enables a better data fitting. Furthermore, without requiring the choice of a specific model, the network is designed to perform automatically the so-called estimation of input significance as a result of which the most significant independent variables in the dataset are assigned high synapse (connection) weight values while irrelevant variables are given lower weight values. It goes without saying that the choice and hierarchy of variables on the basis of input significance contributes to the forecasting performance of the network (Andreou and Zombanakis 2006). Finally, the use of ANN does not require any data distribution assumptions for the input data which is a common issue when running a regression (Bahrammizaee, 2010). Finally, there is also evidence that neural networks display a higher forecasting ability when it comes to time series forecasting (T. Hill, et al. 1996, Adya, and Collopy 1998).

III. Theoretical Background and Methodology

IIIa. Theoretical Background

Following Smith (1989) we shall assume that the demand for defence expenditure is represented as follows[5].

$$DEF = f(Y, P, S) \qquad (1)$$

where DEF is a specific country's defence spending depending on income (Y), prices of defence and civilian goods (P) and selected geopolitical variables depending on the country in focus (S). Given the controversial role of prices in the equation as earlier pointed out, (Sandler and Hartley 1995), prices are usually not included as an explanatory variable and the demand for defence expenditure function in its general form reduces to:

[4] In the case of the demand for defence spending function, for example, the use of prices as an explanatory variable is an open issue (Sandler and Hartley 1995).

[5] This model is derived by using a social welfare function which is maximized subject to a number of constraints; both budgetary and geostrategic ones (see Smith, 1980, 1989, for further details).

$$DEF = f(Y, S) \qquad (1')$$

In the case of Greece, following Andreou at al. (2002), we expand (1') to get the following generalised formulation:

$$EQDEF = f(DLGDP, DRPOP, SPILL, THREAT, Z) \qquad (2)$$

where EQDEF stands for GDP share of defence expenditure on equipment procurement, DLGDP is the country's GDP rate of growth, SPILL stands for the spill over benefits as these are denoted by the defence spending over NATO – GDP figures and DRPOP represents the difference of the population growth rates between Turkey and Greece. The choice of the DRPOP has been based on the emphasis on the human resources variables (Andreou and Zombanakis 2000) in a period in which the Turkish side has explicitly underlined its importance[6]. The four-year lag of the dependent variable is used to represent the follow-up of the Hellenic Armed Forces armaments programme (EMPAE), as this is strongly affected by the political cycle[7]. Concerning Z, this has been reserved for dummies capturing various extraordinary major geopolitical and economic events like the Turkish invasion against Cyprus.

The final variable used in the model is THREAT, representing the Turkish GDP share of expenditure on equipment procurement and approximates the pressure exercised on Greece by Turkey. This pressure has been going on even since the beginning of the 50s, but has been culminating during the last two decades, with the Turkish president during his visit to Athens on December 6, 2017 demanding the revision of the Lausanne Treaty of 1923 and the Paris Treaty 1947 which describe the status quo of the Greek islands in the Aegean.

First we need to determine the forecasting ability of our neural network when it comes to the demand for defence expenditure in Greece and the leading input variables contributing to its forecasting performance.

The dataset used in this study contains the following variables as these are described in Table 1 and is composed of 58 observations covering a period between 1960 and 2018.

[6] In fact during his speech in Eskişehir, in March 2017, the Turkish president urged "his brothers and sisters in Europe" to "have not just three but five children," thus beginning a baby boom in their new countries.

[7] The effect of the political cycle is especially pronounced when it comes to recording transactions on importing defence equipment. Depending on whether the recording system is based on accruals or payments the political cost involved in terms of a "guns versus butter" logic dilemma will burden the ruling party during the period under consideration.

Table 1: The Data Set

Code	Data Series	Source
EQDEF	Greece: Expenditure on Defence Equipment / GDP	NATO and SIPRI
SPILL	NATO Defence Expenditure / GDP	NATO and SIPRI
DLGDP	Rate of change of Greek GDP	ELSTAT
THREAT	Turkey: Expenditure on Defence Equipment / GDP	NATO and SIPRI
DRPOP	Turkey-Greece: Difference of Population Growth Rate	UN STATISTICS

III. b. Methodology

The neural network model has been estimated through the Keras Python library (Chollet et al., 2015). We used several alternative configuration schemes when it comes to the number of hidden layers and the neurons in each hidden layer. Through this process we were able to achieve performance and to also compare how the different network architectures perform on this dataset. The input and output data series are normalized in the range [0,1], while we used Adam as optimizer since it has been shown to be more efficient and it can have a superior performance compared to other optimization algorithms (Kingma & Ba, 2014). Regarding the activation functions, we use ReLu for the neurons in the hidden layers and Sigmoid for the neuron in the output layer.

Each input variable is associated with one neuron in the input layer. The frequency of the data is annual and the observations are split to 80% in-sample / training and 20% out-of-sample / testing. Determining the number of hidden layers and neurons in each layer is a difficult task and it plays a highly significant role in the performance of the model. If a hidden layer contains too few neurons, a bias will be produced due to the constraint of the function space which will result in poor performance. On the other hand, if too many neurons are used, overfitting might be caused and the amount of time needed by the model to analyze the data will increase significantly, which will not necessarily lead to convergence. We therefore, tested the model performance of various combinations of hidden layers and neurons in each hidden layer, in order to obtain the best forecasting performance.

The number of iterations/epochs that present the data to the model also plays a significant role during the training phase. The training of the model was configured to stop if the error metric of the model, calculated on the test set, did not decrease more than 0.0001 in 10 successive epochs or when a limit of 10,000 epochs was reached, and the model was saved for later use. In Figure 1 we display how the error metric fell and reached the optimal number of epochs. However, it should be mentioned that a large number of epochs might cause overfitting and the model will not be able to generalize.

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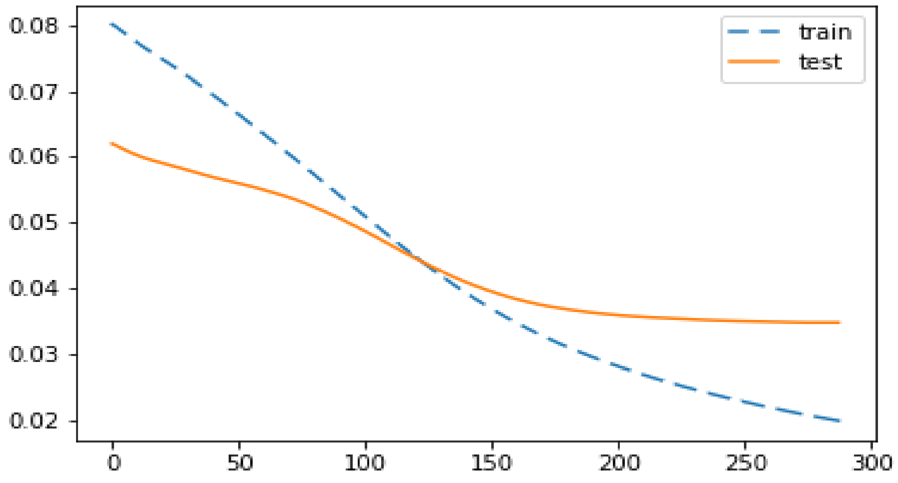
Figure 1: Training and Testing Dataset Error during Model Training



The issue of overfitting can be overcome by evaluating the out-of-sample forecast performance of the model through the usage of a testing set. The testing set contains unseen parameters that were not included in the dataset during the training phase (Azoff, 1994). If the network learned the structure of the input data instead of memorizing it, it performs well during the testing phase. On the other hand, if the model did memorize the data then it will perform poorly on the out-of-sample forecast. Therefore, the optimal network architecture is generally based on the performance of the out-of-sample forecast, assuming that the learning ability was satisfactory.

The out-of-sample forecast performance is evaluated using three different types of forecast evaluation statistics. The evaluation statistics used is the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Theil Inequality Coefficient (Theil's-U). We employ various evaluation statistics since there are certain similarities and differences in each error statistic. To be more specific, all error statistics overcome the cancellation of positive and negative errors during their summation; however, they do not take into consideration the scale of the series that is tested, while Theil's-U does. While in the case of Theil's-U, the series is always bounded between 0 and 1. When comparing the Theil's-U, one looks if the value of the Theil's-U is as low as possible.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t^f - x_t)^2}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|x_t^f - x_t|$$

$$Theil's\,U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t^f - x_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t^f)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t)^2}}$$

where x_t^f is the forecasted value, x_t is the actual value when pattern t is presented and T is the total number of observations.

IV. Results

IV. a. ANN Out- of – Sample Forecasting

Table 2 presents the out-of-sample forecast evaluation statistics of the various neural network architectures. It can be observed that despite the limited number of observations the neural network predicts the movements of the series to a quite significant extent. The best forecast is given by the neural network architecture of 5-40-5, which achieved peak performance after 277 epochs of training. To be more specific, the best forecast has a RMSE of 0.1858, MAE of 0.1215, and a Theil's-U of 0.1866. It is important to note that the Theil's-U value is significantly less than 1. We also present a graph of the best forecast made by the optimal neural network architecture (Figure 2).

Table 2: Neural Network Out-of-Sample Errors

Neural Network Training Output			
Network Architecture	**RMSE**	**MAE**	**Theil's-U**
5-5-5	0.192486	0.141149	0.195553
5-10-5	0.192710	0.129544	0.192350
5-20-5	0.189457	0.122309	0.189630
5-40-5	**0.185800**	**0.121473**	**0.186643**
5-80-5	0.187447	0.122719	0.188300
5-5-5-5	0.204008	0.149236	0.207757
5-10-10-5	0.200814	0.144117	0.205937
5-20-20-5	0.198275	0.127101	0.198514
5-40-40-5	0.193471	0.124721	0.194643
5-80-80-5	0.192268	0.119817	0.191964

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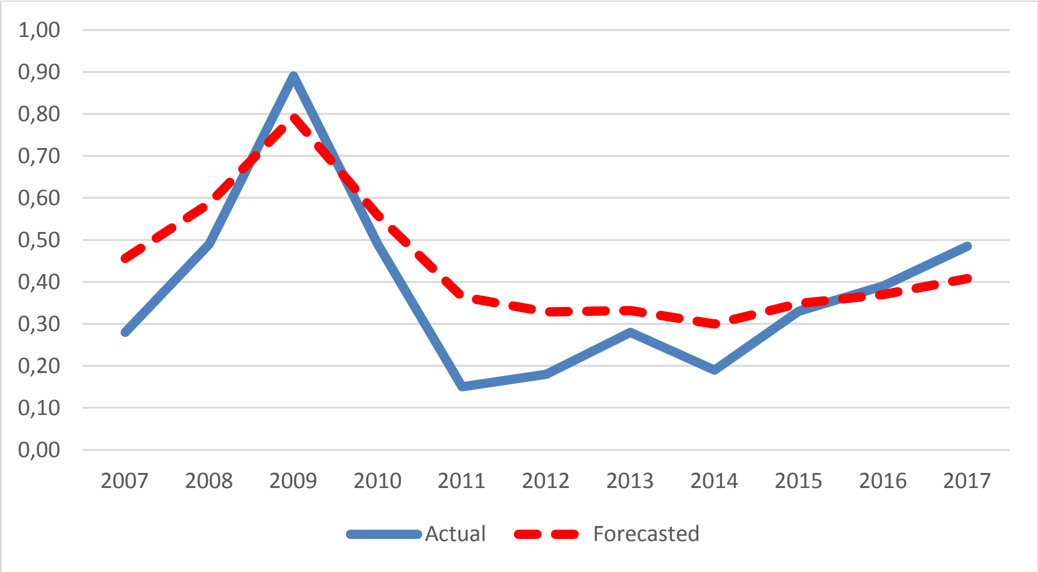
Figure 2: Actual and Forecasted Values of Equipment Defence Spending



IV. b. Determining the Input Significance.

An important aspect of our study is the determination of the significance ordering of the input variables. To be more specific, the input variables that are most significant are those that contribute mostly to the forecasting process. This process is also carried out in Andreou and Zombanakis (2000) study and is explained extensively in Azoff (1994). The significance of the input variables is determined through the sum of the absolute values of the weights fanning from each input variable into all the nodes in the first hidden layer. The input variables that have the highest connection strength are the ones that contribute significantly to the forecasting process. The analytical technical background behind this process is beyond the scope of our study, since the reader may refer to Azoff (1994) for further information.

To train the model, our dataset was split in a training dataset, which consisted of 45 (or 80%) of the observations and a test dataset which consisted of 12 (or 20%) of the observations. The datapoints were assigned to the training and the test dataset randomly, instead of using the first or the last twelve datapoints, because during training the error of the model is calculated on the test dataset and evaluating the performance of the model on a narrow time period is not an accurate predictor of the performance of the model over all the data. Moreover, given that the most recent observations are descriptive of the current situation in Greece, excluding them from the training dataset would negatively impact the forecasting ability of the model. The input significance ordering of the variables used in forecasting the equipment defence of Greece is an important part of our study. The reason is because not only does it show which variable contributes mostly to the forecasting of the variable of interest, but also because inferences can be made on the ordering of the variables that mostly affect the equipment defence spending of Greece.

As earlier stated, the input significance ordering is obtained through the summation of the absolute values of the weights of each input to the neurons of the first hidden layer. Once this process is complete, we rank the variables in a descending order to obtain a clear picture of the most significant variables. The results are presented in Table 3 with W denoting the weight of each variable that appears as a subscript.

Table 3: Ordering of Neural Network Weights

Estimation of Input Significance
$W_{spill}>W_{threat}>W_{drpop}>W_{dlgdp}$

According to the optimal forecast generated by the neural network architecture of 5-40-5, the input significance ordering is $W_{spill} > W_{threat} > W_{drpop} > W_{dlgdp}$. It is interesting to see that the Greek GDP growth rate ranks last in this input significance ordering scheme, pointing to its secondary importance as a determinant of defence equipment purchases. By contrast, the Turkish threat as approximated by the specific country's military spending on equipment, as well as the population rate differential between Turkey and Greece are clearly more important in determining decisions on Greek defence equipment purchases. The performance of spill -over benefits accrued due to the country's NATO membership ranks at the top position, maybe due to the fact that both Greece and Turkey are NATO members[8].

Table 4: Input Significance Ordering

VARIABLES RANKING	ANN
1	SPILL
2	THREAT
3	DRPOP
4	DLGDP

[8] The fact remains, however, that the role of NATO and its spillover benefits for Greece has been questioned since 1974 and the Turkish invasion to Cyprus, following which Greece withdrew from the NATO military structure for a period of six years.

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V. Policy Implications and Forecasting

V. a. Policy Implications

Table 4 sums up the results of the input-significance ordering procedure using ANN. It is evident that THREAT which is approximated by the Turkish defence spending on equipment features at a leading position of our hierarchy ordering preceded only by the NATO spillover benefits. On the human resources side, another variable related to Turkey, namely DRPOP which stands for the difference in population growth between Turkey and Greece is at the third position of the hierarchy ordering[9].

Contrary to expectations the last determinant in the stepwise input-significance ordering concerning Greek defence equipment procurement is the country's GDP growth. The poor performance of the GDP growth in this input-significance ordering can be attributed to two reasons: First, the percentage of GDP channeled to defence equipment procurement has been fluctuating between 0.15 and 0.39 during the past few years, figures too small to underline a high input significance rank between defence expenditure and economic growth. Second, the contribution of the domestic defence industrial base to the EMPAE[10] leaves a lot to be desired, represented by a one-digit percentage figure. Had the presence of the domestic defence industry in the procurement programmes of the Hellenic Armed Forces been more pronounced the link between defence spending on equipment and the GDP growth would have been stronger as the output of the domestic defence industry contributes to the performance of the entire economy (Andreou et al. 2013)**.** By contrast, the link between military spending and domestic defence industrial base in Turkey is much stronger, given that more than 50% of their armed forces requirements are met by the Turkish industry[11].

Focusing on the Turkish defence expenditure represented by THREAT, its predominance in the ordering of input significance deserves special attention as it is supported by the increasing pressure exercised from the part of Turkey regarding the status quo of both the Aegean and the Eastern Mediterranean (see Table A. II. 1 in Appendix II and Figure 3 below), with the Turkish defence minister Hulusi Akar raising claims on what he called "Blue Homeland" in December 2018. Figure 3, in particular, shows how the Turkish Airforce (THK) hostile activity expressed as ICAO and FIR violations, armed aircraft and engagements (dogfights) in the Hellenic airspace reached an overall maximum during the recent past[12.]

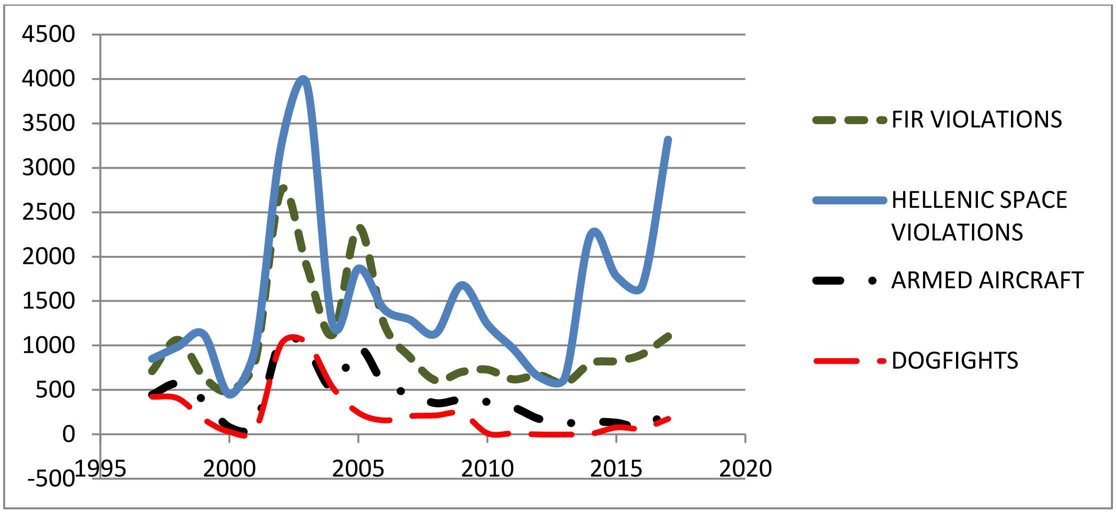
[9] As a latest update the Turkish population increased to 82.8 mill. In 2017, an increase of 3.6% compared to 2016. By contrast, the tendency of the corresponding Greek figures is slowly but steadily declining.

[10] Medium Term Developments and Modernisation Programme of the Hellenic Armed Forces.

[11] In fact, during a recent speech in Ankara (October 2018), Erdoğan pointed out that the development of a sound defence industrial base is a prerequisite for a peripheral military power in the S.E. Mediterranean.

[12] The emphasis given to FIR and ICAO violations at the expense of engagements during the last few years may be due to the fact that a large number of experienced pilots have left the THK following the July 2016 coup attempt. In addition recent experience indicates a shift to alternative forms of aggression

Figure 3: THK Activity in the Hellenic Airspace



Source: HAF, NATO

V. b. A Forecasting Exercise

The dataset for the training of the model consists of a set of inputs, and their corresponding labels, or expected output. Our dataset uses as inputs the values of the five variables for each year n while the values of the variables of the next year $n+1$ were used as the corresponding expected output. This way, each model was trained to accept as input values for the five variables and forecast the values of the five variables for the following year. The models were assessed using error metrics and the best performing model was selected to perform a forecast of the Greek defence spending on equipment for the years 2019-2022.

For the purpose of this study we adopted two forecasting scenarios, the first one involving a conservative Turkish defence equipment procurement strategy and a second one regarding an aggressive defence equipment purchases strategy. The former is introduced by assigning a purchases value corresponding to 0.3% of GDP which represents one of the lowest values during the last few years. By contrast the aggressive defence procurement strategy

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involving mainly naval tactics. Thus, on February 12, 2017 a Turkish coast guard vessel rammed a Greek one while performing what the Greek coast guard called “dangerous manoeuvres inconsistent with international collision avoidance practices.” The fact that the incident took place near Imia, a pair of Greek islets the ownership of which Turkey has disputed for 20 years, points to a territorial power play. The threat mix involves, in addition certain rather unorthodox methods like the arrest of two Hellenic Army officers during a border patrol in the north on February 28 and their imprisonment since then without pressing any charges.

increases this figure to 0.8% of GDP[13]. To achieve this, the 2018 data were used as inputs to obtain the forecasted values for 2019 which were in turn used as inputs, after setting the threat value to 0.3 or 0.8 depending on the forecasting exercise, to obtain the values for 2020 and this process was repeated for the years 2021 and 2022. The results of the EQDEF forecasting exercises are presented in Table 5 and Figure 4.

The forecasted values of the Greek defence expenditure in the context of the arms race in which the country has been entangled against Turkey do not reveal any pronounced sensitivity to the scale of the Turkish procurement programmes. By contrast, they reflect almost accurately, the provisions of the 2019 defence budget for the Defence Ministry (Ministry of Finance 2017) which offer little room, if in fact any at all, for major defence equipment purchases[14].

Table 5: Greek Defence Spending on Equipment (%GDP)

Forecasts under Alternative Scenarios

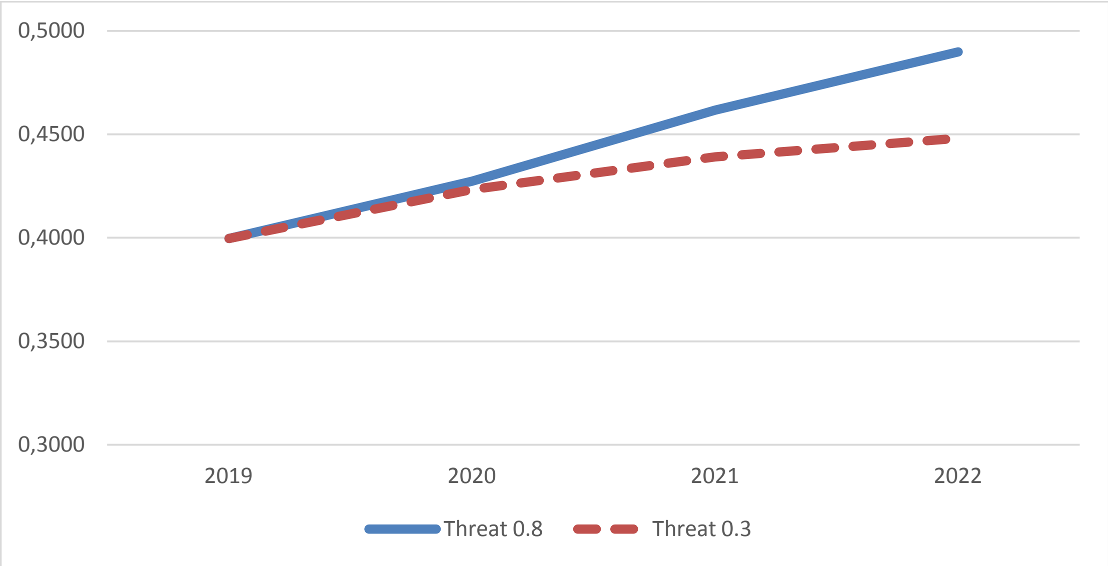
YEAR	EQDEF : ESCALATING TURKISH POLICY	EQDEF : CONSERVATIVE TURKISH POLICY	DIFFERENCE
2019	0.3996	0.3996	0.0000
2020	0.4273	0.4234	0.0039
2021	0.4617	0.4391	0.0225
2022	0.4897	0.4480	0.0417

[13] This figure means that until the conclusion of the % 150 - billion Turkish procurement programme there will be about $40 billion left to spend. This figure barely covers the cost of a helicopter carrier ($2 bill), the S-400 missiles ($2.5 bill.), 145 attach helicopters ($4 bill.), 1,000 battle tanks ($6 bill.), 100 F-35 fighters ($1.5 bill.), 6 t-214 submarines ($4 bill.) and a number of other programmes involving the TF-X domestically produced aircraft, the modernization of the f-16 fleet and the MILGEM corvettes.

[14] The 2019 budget provides €3.3 bill. to the Ministry of Defence with the funds allocated to equipment procurement not exceeding €1 bill, amounting roughly to 0.5% of GDP. Needless to point out therefore that any comparison between the Greek and the Turkish side as regards defence procurement spending figures is pointless.

Figure 4: Greek Defence Spending on Equipment (%GDP)

Forecasts under Alternative Scenarios



VI. Conclusions

The aim of this paper has been to investigate the possibility of increased defence expenditure from the part of Greece once the country's economy recovers from the prolonged crisis, an increase which has been against the Troika policy recommendations. The results derived point to a number of interesting conclusions:

First, the forecast shows that there will be an increase of defence expenditure on equipment procurement in the next few years.

Second, a return to positive growth rates is expected to bring about rather low, if any at all, increases as regards defence spending on equipment. This is due to both the restricted funding of the Defence Ministry requirements as well as the limited contribution of the domestic defence industrial base to the EMPAE programmes and consequently to the country's economic growth.

Third, the main source of defence spending increases in the future is the corresponding expenditure from the part of Turkey, in the logic of an arms race environment which has been threatening the NATO cohesion ever since 1974 when Greece had withdrawn from the alliance military structure for a period of six years. Such an environment accentuates the already existing frictions between Turkey and a number of the remaining NATO members for a wide selection of reasons. The increasing population differential growth rate between Turkey and Greece simply adds to the threat, ranking third in the input significance ordering.

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Fourth, the pressure exercised in such an environment from the part of Turkey has increased since the beginning of last decade making the follow-up cost considerably heavy for Greece to sustain as the resource availability is constrained by the tight annual budgets.

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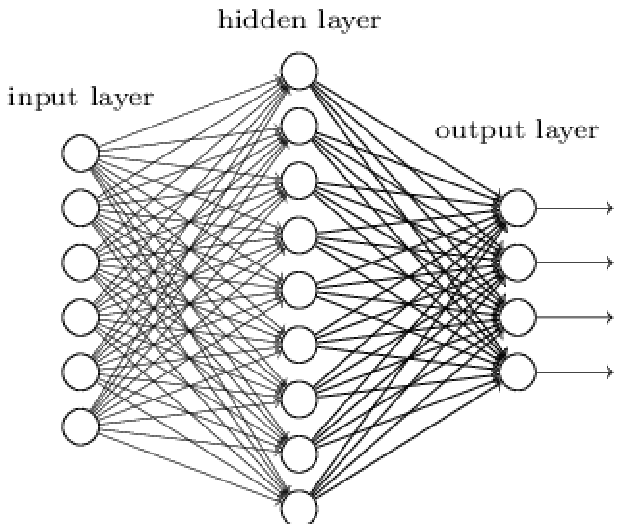
Appendix I. NN Briefing

Artificial Neural Networks, which belong to the data science approach and not on the model driven approach, are one of the widely used models for data science applications. They are loosely based on the biological nervous system and brain functions, meaning that they employ certain general purpose algorithms to analyze the input data provided. The structure of an Artificial Neural Network contains the input layer, the hidden layers and the output layer. Each layer contains several nodes or neurons. Each neuron connection is assigned a weight that is based on its relative importance compared to the other inputs. The calculation of the weights that creates the input-output mapping are what solve the high dimensional, non-linear system identification problem. However, the model adjusts its weights in order to minimize the errors in the results. A commonly used process for the training is back-propagation, which is technically the derivative of the errors with respect to the weights $\frac{\mathrm{dError}}{\mathrm{dWeights}}$. An example of an m-d-q neural network architecture is displayed in Figure 5 where m are the inputs, d are the number of neurons in the hidden layer, and q are the output neurons. In our study we estimate an m-d-5 network architecture to forecast the behaviour of our time series.

Figure A. I. 1: Example of a Neural Network Diagramme



The input data is analyzed by the neurons inside the hidden layers through the utilization of activation functions such as Sigmoid and ReLu (Hahnloser et al. 2000) The mathematical form of the Artificial Neural Network is presented below:

$$y_t = w_o + \sum_{j=1}^{q} w_j \times g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} \times y_{t-1}\right) + \epsilon_t$$

where $w_{ij}(i = 0,1,2,..,p, j = 1,2,..,q)$ and w_j $(j = 0,1,2,\ldots,q)$ are the connection weights/biases, p is the number of input neurons and q is the number of the hidden nodes. The output of the model is y_t and the input variables which are the previous values are y_{t-1}. The error term is ϵ_t which is the difference in the forecasted and actual values of the output and g is the activation function of the model. It should be mentioned that a commonly used parameter by artificial neural networks is the bias factor that has a fixed input value of 1 and it feeds into all neurons in the hidden and output layers with adjustable weights. Its significance is that it shifts the activation function which results in an increase in the accuracy of the data.

I. 1. System Design

The input data, $x = \{x(t): 1 \leq t \leq N\}$ is split into a training set $x = \{x(t): 1 \leq t \leq T\}$ and a testing set $x = \{x(t): T < t \leq N\}$, where N is the length of the series. The training set is used to train the network at a certain level to achieve convergence based on some error criterion. This is achieved by presenting the input and output data L-times to the model and have the

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learning algorithm adjust its weights. The number of times that the data is presented is called epochs and the output neuron is basically the predicted values that the model predicts. The process of back-propagation is carried out by an optimizer such as Adam. The range of predicted values is between [0,1] by the implementation tool used. Therefore, the values x_t of both the training and testing set is normalized by taking the ratio $\frac{x_t - x_{min}}{x_{max} - x_{min}}$, in order to avoid negative values. The predicted values x_t can be restored by taking the inverse transformation $x_t^f * (x_{max} - x_{min}) + x_{min}$.

Appendix II. The Greek / Turkish Conflict in Figures

Table A. II. 1: Turkish Air Force Activity in the Hellenic FIR

YEAR	FIR VIOLATIONS	HELLENIC SPACE VIOLATIONS	ARMED AIRCRAFT	DOGFIGHTS
1997	712	849	448	425
1998	1064	986	574	405
1999	648	1125	384	171
2000	487	446	82	30
2001	826	976	105	53
2002	2742	3240	1062	1017
2003	1891	3938	970	1032
2004	1121	1241	521	528
2005	2330	1866	977	244
2006	1237	1406	567	159
2007	868	1289	464	207
2008	608	1134	353	215
2009	703	1678	395	237
2010	729	1239	367	13
2011	620	962	307	13
2012	667	646	176	1
2013	577	636	129	0
2014	801	2244	145	8
2015	826	1779	133	80
2016	902	1671	86	68
2017	1103	3317	257	176

Source: Hellenic General Staff

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