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THE GREEK CURRENT ACCOUNT DEFICIT: IS IT SUSTAINABLE AFTER ALL?

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ABSTRACT

The large Greek current account deficit figures reported during the past few years have become the source of increasing concern regarding its sustainability. Bearing in mind the variety of techniques employed and the views expressed as regards the analysis and the assessment of the size of the current account deficit, this paper resorts to using neural network architectures to demonstrate that, despite its size, the current account deficit of Greece can be considered sustainable. This conclusion, however, is not meant to neglect the structural weaknesses that lead to such a deficit. In fact, even in the absence of any financing requirements these high deficit figures point to serious competitiveness losses with everything that these may entail for the future performance of the Greek economy.

Keywords: Neural Networks, Current Account Deficit Sustainability

JEL classification codes: C45, F32.

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1. Introduction

The question whether the Greek current account deficit is sustainable has triggered considerable debate during the past few years, which has also highlighted a number of serious weaknesses of the Greek economy. We have thought, therefore, that the reader may find it useful to devote some time to sharing and considering the points raised in this paper concerning this controversial issue.

Let us start, therefore, by a reminder: the Eurozone membership of Greece may have sacrificed a major policy tool, namely the exchange rate, it has however, relieved the economy of any deficit-financing requirements in foreign currency terms concerning its external accounts. Still, the substantial increase of the current account and the fiscal deficits of Greece during the past few years has become a source of concern at both national and international levels as it rings a warning bell concerning the deteriorating competitiveness of the Greek economy which, in its turn, points to the need for serious structural reforms.

The extent to which the government has already embarked on such reforms and the effectiveness of the measures taken is an open issue outside the scope of the present paper, the purpose of which is to focus on the period up to the point in time when these measures may bear fruit and examine the extent to which the sizable current account deficits of the past few years can be considered sustainable over this period. This will require a brief review of the literature on current account sustainability followed by an analysis of the technical background, i. e. a description of the neural network algorithm employed. The final section of the paper will cover the empirical results followed by the conclusions derived.

2. Literature background

The bulk of the literature on the topic predates the current international crisis and the majority of the sources refer to the financing of the US current account deficit, which had recently come to rely, almost exclusively, on sovereign funds, among which the

Chinese ones occupied a leading position. Such sources include Mann (2000) pointing to the fact that the United States spend more than they earn only to support global growth, thus creating a huge trade and current account deficit the sources of which are to be traced in the early nineties (Holman, 2001). There exist some rather rare cases, where such warnings were confronted by reassuring voices like, e. g. Cooper (2001) who feel that the dollar depreciation used as a temporary deficit-restricting device will be of more concern to foreign authorities, who will be compelled to support the U.S. currency by buying dollars in order to prevent further depreciation of the US currency. It is important to note, however, that in this case the author fails to take into account the adverse repercussions of the dollar depreciation on international crude oil prices. More recent contributions include Bergsten and Williamson (2004), Obstfeld and Rogoff (2004), Edwards (2005) and CRS (2005); the first one deals with the determination of the sustainable level of the US current account deficit. Determining such a "sustainability threshold" presupposes defining a sustainable current account deficit as one that "changes in an orderly fashion through market forces without causing jarring movements in other economic variables, such as the exchange rate" (Holman, 2001). This means that such a deficit level is not expected to disturb capital flows and the net international investment position of the economy in a way that will result to substantial adverse repercussions on macroeconomic magnitudes like the exchange rate of the domestic currency, interest rates, consumption or investment.

It is interesting to point out, however, that articles referring to the sustainability problem in general appeared even during the 1980s for a number of country cases (e.g. Makin, 1989); most of them underline the role of the gap between savings and investment opportunities, while others (Milesi and Razin, 1996, or Roubini and Wachtel, 1997) focus on a number of country studies or on the case of transition economies respectively. Baharumshah et al. (2005) consider the current account sustainability question and the constraint which it imposes to a number of East Asia countries, while the case of the UK economy and its Eurozone membership prospects are treated by Church (1999) who seems to be concerned by the unavoidable neutralisation of the exchange-rate policy instrument and the extent to which external balance problems may be treated in such a case. Finally, the contribution of Bussière et al. (2004) is very interesting as it focuses on deriving structural current account positions, i.e. position which can be considered as "normal" from a long run perspective when cyclical effects have died out.

Despite the chronic balance of payments problems facing the Greek economy, the issue of its current account deficit sustainability has been brought forward only during the last decade through a rather small number of papers. Those by Pantazides (1999) and Apergis et al. (2000) agree that the pressure exercised on the burden of the current account deficit and the resulting debt accummulation are not enough to cause serious disturbances on the basic macroeconomic variables of the country's economy and that such a deficit is therefore sustainable. There are papers, however, (e.g. Freund, 2005) which suggest that a generally accepted figure determining the current account deficit sustainability threshold is about 5% of GDP. To the extent that this figure can be considered as applicable to the Greek case, the sustainability of the Greek current account must have become an issue of major concern during the years that follow the publication of the two papers mentioned above. In fact, the year 1999 must be taken to be a benchmark with the deficit exceeding 6% of the GDP and this figure following a sustained upward trend and climbing to an impressive 14.4% in 2008. Since 1999, however, a number of important developments have taken place affecting the structure and statistics of the external transactions of Greece, which have added to the deficit increase due to the competitiveness problems caused by the structural weaknesses of the Greek economy. To begin with, Greece has become a member of the Eurozone since 2001, something which has deprived the authorities from the exchange rate policy instrument while relieving them from answering the question on how to finance external imbalances. In addition, there has been a variety of exogenous influences which added to the current account burden making the question of its sustainability even more difficult to answer. Such influences were: (i) the payments for purchases of ships, which reflected the increased demand for sea transport services, connected to trade with markets like China and India; (ii) the dramatic increases of the international crude oil prices during the recent past, in a context of low price elasticity of demand and heavy energy dependence of the Greek economy in an environment of high growth rates. Finally, there have been radical changes in external sector statistics (the exclusion of capital transfers from the current account, the recording of interest payments on an accrual rather than on a cash basis). All these developments have contributed to further increasing concerns as regards sustainability; thus, it is no wonder that Anastasatos (2008) does not seem to share the optimism of the two sources mentioned above, pointing to the fact that the current account deficit reflects a competitiveness problem which erodes economic growth and increases foreign debt.[1]

The disagreement as to the extent to which the current account deficit of Greece can be regarded as being sustainable, as well as the various figures representing what is supposed to be regarded as a widely acceptable sustainability level are due to a large extent to the variety of techniques used to approach the issue. Pantazides (1999) and Apergis et al. (2000) use the reasoning suggested by Husted (1992) who focuses on the stock of external debt, hence on the accumulation of the annual external transactions deficits, "to decide whether the budget constraint is expected to be intertemporally balanced". Anastasatos (2008), on the other hand points to the inadequacy of the Balassa-Samuelson hypothesis to fully explain the Greek case, and suggests the use of dynamic general equilibrium models as in Blanchard and Giavazzi (2002). Finally, the IMF (2007) paper quantifies the competitiveness deficit by using no less than three approaches, namely the Macroeconomic Balance, the Equilibrium Real Exchange Rate and the External Sustainability Approach. Additional room for disagreement is offered by the extent to which competitiveness is defined as just price and cost competitiveness, or, instead, as also including non-price components like technology, quality, brand name and market knowledge.

Given this wide variety of opinions and methods we have decided to resort to using data-driven reasoning instead of model-based analysis What we have done, in fact, is base our analysis on artificial neural networks (ANN), in order to free it from the constraints imposed by the philosophy and the structure of whatever model were to be selected.

[1] The IMF (2007) tends to agree more or less with Anastasatos (2008), using, however, a variety of methodologies on the subject.

3. Technical aspects

An ANN is a computational model which attempts to imitate biological neural behaviour and, in most cases, is considered as an adaptive system that changes its structure based on external and/or internal information that flows through the network during some learning phase.[2] In fact, an ANN learns by examples and is considered as a modelling technique suitable to treat complex non – linear functions by gathering representative data, and then employing training algorithms to learn the structure of these data. To the extent that the learning process has been considered successful on the basis of a selection of error measures, the system can then extend the behavioural pattern obtained during the learning stage to forecast the future development of the time series under consideration.

Bearing in mind this short technical description together with a more extensive analysis provided in Appendix I, the properties of what Taylor (1995) calls "recently developed sophisticated time-series techniques" seem to be worth benefiting from. In fact the use of such data-driven approaches has been considered preferable to traditional, model-driven approaches used for forecasting purposes, given their advantages as these are extensively analysed in sources like Kuo and Reitsch (1995), Kosko (1992), Patterson (1996) and Haykin (1994). These papers underline the fact that Neural Networks are not bound by the constraints imposed by econometric models. Instead, given that NNs are non-linear they can capture complex interactions among the input variables in a system, thus being very useful in cases in which standard theory cannot conclude as to a specific model structure. This means that in comparison to multiple regression analysis NNs can be more reliable, given that they do not need to rely on any model specification. Thanks to the so-called "estimation of input significance" performed automatically, the most significant independent variables in the dataset are assigned high synapse (connection) weight values while negligible weight values are shown for irrelevant variables. Thus

[2] Given their flexibility, ANN have become an interdisciplinary tool of analysis, having contributed a great deal in areas like Signal Analysis and Processing as well as Process Control and Robotics. In addition they have proved to be very useful in cases of Data Classification and Smoothing, Pattern Recognition, Image and Speech Analysis and Medical Diagnostics. Finally, their contribution to defence issues, as well as to stock market or exchange rate forecasting analysis for loan or credit demand and marketing orientation has been widely acknowledged.

NNs, being adaptive, can be trained, without depending upon prior knowledge of any rules, to learn underlying relationships on the basis of a training data set even when such relationships are difficult to find and describe. Once trained to recognize such relationships, NNs can generalise by processing information that only broadly resembles the original training data set. This is a very useful property given that real world data are often noisy. Similarly, NNs can handle imperfect or incomplete data by providing a measure of fault tolerance, while they can account for any functional dependence thanks to their ability to trace and then learn the nature of such dependence. Finally, thanks to their parallel architecture, NNs can achieve high computational rates while posing no conditions on the predicted variables.

4. Empirical investigations and results

The possibility of a long – run relationship between payments for imports and proceeds from exports of goods and services such that it can safeguard that their future trends will not diverge significantly, can be considered to guarantee the sustainability of the current account deficit (Pantazidis 2000). Using the ANNs jargon we shall investigate the extent to which a time series of goods and services export proceeds can be used to predict the corresponding series of goods and services import payments. In such a case, provided that the forecasted series is successful in following the behaviour of the actual values, one can establish the prerequisites for a stable difference between the two series in the long run, something that can safeguard the sustainability of the current account deficit. The experiments carried out involved the creation and execution of several neural network models. After preliminary investigations, it was decided to describe in detail only two of the experiments, specifically two multilayer perceptrons using a Levenberg - Marquardt backpropagation algorithm (Levenberg, 1944) and a Gradient descent with momentum weight and bias learning function, both having one hidden layer. The architectures of the two are presented in Table 1.

Table 1: Artificial Neural Network Architectures Employed

NETWORK ARCHITECTURE	NUMBER OF NEURONS INPUT LAYER	HIDDEN LAYER	OUTPUT LAYER
NN-1	2	4	1
NN-2	3	6	1

Both neural networks used a Bank of Greece dataset of 49 observations, from 1960 until 2008, consisting of Greece's value of goods and services exports (X) used as input and the corresponding value of goods and services imports (M) used as target values. The values were normalised before being inputted to the networks using formula (5.1) below in order to remove the underlying trends in the economic values.

$$\log\left(\frac{X_t}{X_{t-1}}\right), \qquad (5.1)$$

Furthermore, a sliding window technique was employed in order to take into account the fact that the data essentially form a time series. This, in turn, determined the number of neurons in the input layer. Specifically, NN-1 used a sliding window of size two, meaning that the input vector consisting of $\langle X_{t-1}, X_t \rangle$ was used to predict the target M_t. Likewise, for NN-2, with a sliding window of size three, the input vector $\langle X_{t-2}, X_{t-1}, X_t \rangle$ was used to predict M_t. Finally, we should note here that the input and target vectors were separated into three sub-datasets:

- Training set (60%). The training set contains a set of input vectors that are given to the network for learning purposes and adjusting the weights between neurons to create the final network model.
- Validation set (20%). The validation set is used to adjust various parameters of the network while learning.

- Testing set (20%). The testing set is not used in the learning phase of the network. Its purpose is to evaluate the network's performance, i.e. its ability to generalise [5].

The implementation of the experiments was carried out using MATLAB® R2008a and ran on a machine with a 2.00 GHz processor and 1.00 GB RAM. For each architecture, 200 networks were used and, once initialised, all networks were fed the input vectors and left to train for 1000 epochs using the corresponding training dataset. After network training was complete, the networks were subsequently tested using the (previously unseen) testing dataset to see if they could correctly produce the desired target values. In both training and testing phases, the networks produced an output for each corresponding input vector and this output was measured to determine how close a specific network came to predicting (or failed to predict) the desired target value.

Subsequently, we employed a number of widely-used error measures described in Appendix II, in order to calculate the networks' errors. The various error measures that evaluate results during the training and testing phases of the two network architectures were analysed and compared mainly regarding their Mean Relative Error (MRE) values. Despite the fact that networks manage to learn, the MRE values produced during their testing phase indicated that the networks were not able to generalise, since for the majority of networks in both architectures the error measures yielded MRE values greater than one, while at the same time all other error metrics were confined to low values.

In order to identify the cause or causes of high MRE values during testing, a simple numerical analysis of the sample data was carried out to see if the sample data included any outliers. Indeed, a small number of observations, mainly towards the end of the time series, have been traced to introduce outliers, whereby the increase or decrease of imports followed – correspondingly -- a decrease or increase of exports. This is to be expected given the length of the time series used and the considerable number of breaks, due, among other things, to statistical methodology adjustments undertaken by the producer of the data (i.e. the Bank of Greece) mainly in order to comply with the IMF 5th

Manual guidelines (IMF 1993).[3] Also, such breaks inevitably occur as a result of the speculative attack against the drachma following the short-term capital movement liberalization on May 1994, the beginning of the Eurozone membership of Greece, the Olympic Games effect and, as earlier pointed out, a number of changes in statistical methodology (like the measurement of interest payments on an accrual, rather than a cash basis, the exclusion of the capital transfers from the current account items and the use of surveys to measure travel statistics).[4] With the removal of these sample data, the network models were re-executed and their results are presented in Table 2.

Table 2. Network training and testing errors

		NN-1 (2-4-1)						NN-2 (3-6-1)				
		NRMSE	CC	MSE	MRE	MAE		NRMSE	CC	MSE	MRE	MAE
Training	A	0.507	0.855	0.003	0.374	0.044	D	0.378	0.939	0.002	0.333	0.033
Testing		0.615	0.832	0.003	0.499	0.040		0.962	0.681	0.008	0.464	0.071
Training	B	0.498	0.861	0.003	0.380	0.044	E	0.214	0.975	0.000	0.271	0.0220
Testing		0.612	0.832	0.003	0.492	0.050		0.602	0.823	0.003	0.472	0.053
Training	C	0.538	0.837	0.004	0.452	0.046	F	0.263	0.963	0.001	0.256	0.0226
Testing		0.566	0.837	0.002	0.447	0.042		0.718	0.782	0.004	0.476	0.058

Table 2 displays the error measures calculated from a sample of six different networks trained and tested: A-C under NN-1; D-F under NN-2. Both architectures produced variable error measures with their respective networks. The Correlation Coefficient (CC) values of NN-1 networks (A-C) fluctuate around 0.85 and those for NN-2 networks (D-F) about 0.95. The CC values denote a positive correlation, whereby the networks are able to identify the oscillations between increases and decreases of the

[3] Despite the effectiveness of the smoothening process used by the Statistics Department of the Bank of Greece when adjusting the balance of payments series backwards aiming at smoothening out the breaks in the series following all methodology changes, there still seem to be a few such breaks left.

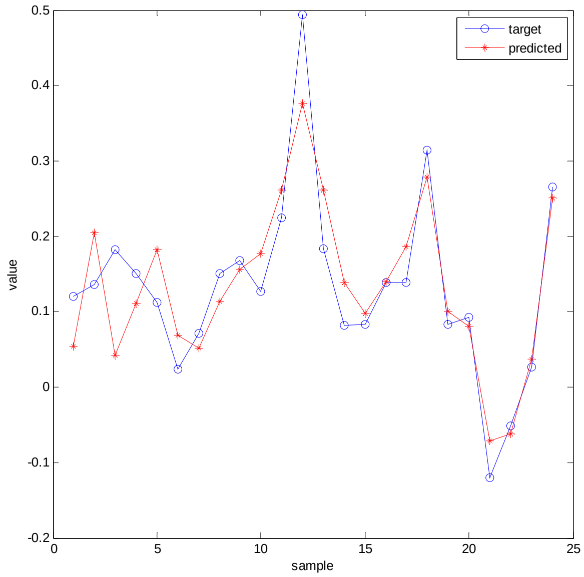
[4] The import and export data series have been revised backwards to the furthest possible extent aiming at smoothening out the effects of such changes on these series.

real data. More encouragingly, during their training phase the networks of both architectures managed to yield low MRE values (between 0.37 and 0.45 for NN-1 networks and between 0.25 and 0.33 for NN-2 networks), which suggest that adopting artificial neural networks to predict the Greek import payments with regard to its export proceeds provides a solid approach.

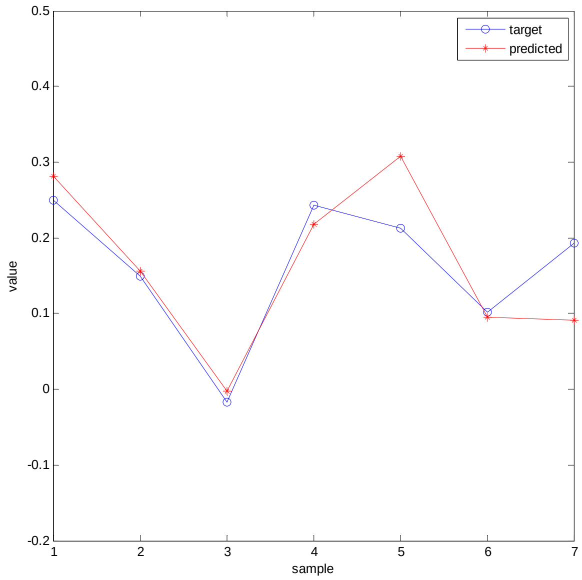
Furthermore, it is clear that the removal of the specific outliers contributes to the low MRE values during the networks' testing phase at the same time retaining the good performance during training. The testing of NN-1 networks produces MRE values of 0.45-0.49, and NN-2 networks around 0.47. The testing MRE value is higher than the training MRE value as this is normal behaviour exhibited by artificial neural networks, but reassuringly both values are less than one. Likewise, NN-2 also has training and testing MRE values lower than one, with the latter, however, being greater than the former.

Figure 1 displays a graphical representation of network A showing how the network's outputs matched against the actual target values in its respective training and testing phase. These results support our argument for a stable difference between the values of exports and imports in the long run, something that can safeguard the sustainability of the current account deficit[5].

[5] This reasoning is often used in the literature (e. g. Pantazides, 1999). Using it, however, presupposes that the historical series of deficit figures used as input have been considered sustainable and consequently any deficit close to these figures is also sustainable.



(a) Training phase



(b) Testing phase

Figure 1. Actual target values versus predicted network outputs for network A (2-4-1 architecture)

5. Conclusions

This paper has looked into the issue of Greek current account sustainability by investigating the extent to which a time series of goods and services export proceeds can be used to predict the corresponding series of goods and services import payments. Our experiments have relied on using Artificial Neural Network technology in order to show that the forecasted series has been successful in following the behaviour of the actual one, indicating that the difference between the two series can be considered as being stable in the long run, something that can safeguard the sustainability of the current account deficit. While this conclusion seems to agree with the findings of part of the sources in the literature, one must bear in mind that all four contributions dealing with the Greek case could not possibly incorporate the effect of the latest crisis and the forecasts for a recessionary outlook. The paper by Anastasatos (2008), in particular, was written at a point at which the crisis seemed to be withering out and things were looking up in the international economic environment.[6]

We believe, however, that the recessionary environment which is forecasted to follow this crisis is expected to "deflate" the Greek external account items to the extent that each of these items is affected mostly by exogenous disturbances.[7] Indeed, relieving the current account items from effects like the oil price increases and the high demand for sea transport services following the substantial rates of growth observed in the

[6] For example the BEA monthly report for late July 2008 pointed to an acceleration of the US rate of growth at a quarterly annualised GDP growth rate of the order of 2%! During that period (mid - 2008) the $ / € rate started showing signs of reversing its upward trend, while oil prices were still rising reaching record levels. In short the general feeling was that one might be speaking about a deceleration but certainly not a recession in terms of a forecast.

[7] Recent developments in the international markets suggest a considerable reduction of the trade balance burden during the next couple of years in a recessionary environment as a result of the rapidly declining crude oil prices and the fall in net payments for purchases of ships. Indeed, orders for the construction of new vessels are reported to be more than 60% lower compared to 2007 mostly due to liquidity problems. In addition, there have been quite a few cancellations of shipbuilding contracts as a result of banks' liquidity shortages affecting both the ship-owners' borrowing possibilities and the shipbuilders' investment programmes aiming at installation expansion (Data by the Hellenic Ship-owners' Association / Moundreas Shipbrokers). On the services side, the Baltic Dry Index (BDI) and the Baltic Dirty Tanker Index (BDTI) fall during the last few months is expected to affect the sea transportation revenues. The fall of the $ / € rate, however, given the dollar denomination of maritime transportation transactions, together with certain long-term forecasts pointing to an increase of the Greek-owned fleet, could restrict the adverse impact of the freight rates fall during the forecasted period. The forecast for the travel receipts, by contrast, is rather disappointing.

developing world during the past few years reduces its deficit to something like 5% to 7% of GDP,[8] which may be regarded as a "core deficit" figure. It is important to stress at this point that these scenaria include the effect of these exogenous variables on both the import and the export side, with the deficit reduction being expected given that the import bill is usually a multiple of the export proceeds in most cases. So, the next question to tackle is the extent to which such "core deficit" figures are indeed sustainable. Given that the variety of opinions on the subject does not contribute to setting a well-defined sustainability threshold, we are inclined to stick to Holman's view (Holman, 2001) according to whom a sustainable current account deficit is one that is not expected to result to substantial adverse repercussions on macroeconomic magnitudes like the exchange rate of the domestic currency, consumption or investment. In that sense, we must conclude that developments in the macroeconomic fundamentals of the Greek economy for the period under study support the findings of this paper.

The fact is that the persistence of these high "core deficit" figures, though it may not raise any worries about its financing requirements, does highlight, however, the dominant role of the endogenous structural weaknesses mentioned earlier in preserving the tendency for such deficits. The symptoms of these structural weaknesses appear in the form of import price inelasticity and lack of import substitution, together with high income elasticity of imports on one hand and the well-known competitiveness problems on another, mentioned in section 2.

One must be very careful at this point, however, not to reverse the causality order when considering relationships involving such variables. In fact, the various structural weaknesses of the Greek economy that Anastasatos (2008) points to very successfully have resulted to disturbances in magnitudes like consumption and investment and these, in their turn, to high current account deficits. Moreover, the recessionary environment which the international economy is about to face, at least for the next year or so, is expected to affect the real economy and, therefore, such fundamentals to a higher extent.

[8] Anastasatos (2008) seems to agree with our estimate, as he refers to a current account deficit of 5.4% of GDP.

These changes, however, must be no means be attributed to the heavy current account burden.

We need to emphasize once more that the conclusion of this paper arguing in favour of the Greek current account deficit sustainability, must not be considered as disregarding the need for serious structural reforms required to eliminate the fundamental problems pointed out by Anastasatos (2008). In fact we strongly agree with his recommendations requiring, among other measures, the elimination of the various market rigidities, the emphasis on high technology production, the attraction of export-oriented FDI and the reduction of the heavy energy dependence of the Greek economy. These recommendations have repeatedly been put forward in the past by the Bank of Greece (Bank of Greece, 2008 I and II).

Appendix I: Technical background

Neurons in a network are organised in sets of layers. The first layer is called the input layer and is used for data input while the final layer is called the output layer._In addition, between these two, there may be a set of hidden layers the function of which is to identify a non-linear mapping of the values obtained from the input layer to the desired values outputted by the network. This is performed by presenting patterns of input-output values to the network and then calculating adjustments of the weights connecting the hidden neurons based on a training algorithm assessing the difference between the output of the network and the desired sample value in an iterative manner. Neurons between layers can be fully or partially connected, depending on the linkage of neurons of one layer to neurons of a subsequent layer. In a simple feedforward network, neurons of a specific layer are only connected to neurons in the immediately proceeding layer allowing the information to flow only in a forward direction. However, there may also be optional connections from neurons of one layer to neurons of a previous layer permitting the information to flow through neurons in both directions. This type of network is known as a feedback or recurrent network (Vlachavas et al, 2002).

Artificial Neural Networks (ANNs) perform two basic functions; learning and recalling. Learning is the process of modifying the weights of the network so that an output value is produced for a given input vector, whereas recalling is the process of calculating an output value given an input vector and weight values (Vlachavas et al., 2002). Hence, ANNs can be classified into three categories based on the approach used to modify weights during its learning phase: (1) supervised learning, (2) reinforced (graded) learning, and (3) unsupervised learning. We focus only on the first category since our experimental approach adopts ANN trained in a supervised manner.

In supervised learning, pairs consisting of input vectors and their corresponding targets are fed into the network; with its current weights the ANN produces an output. Outputs are matched against their respective targets and the difference, should there be one, is called the “error”. Based on this error, together with a learning algorithm, the ANN adjusts its weights in order to attempt to produce the correct output. The error minimisation process requires a special circuit known as a teacher (or supervisor) hence the name supervised learning (Vlachavas et al, 2002). Input vectors and the corresponding targets can be used to train a network for many purposes. For example, they can be used to approximate a function, associate input vectors with specific output vectors, or classify input vectors in a predefined way (Matlab, R2008a).

Feedforward networks are one of the many types of ANNs. They consist of an input layer, an output layer and one or more hidden layers. One of the simplest feedforward networks is the Perceptron, introduced by Rosenblatt (Rosenblatt, 1958). Perceptrons are fast and reliable networks (Matlab, R2008a)**,** however inadequate for solving complex problems. In order to overcome this limitation, Multilayer Perceptrons (MLPs) were introduced. In general, MLPs are composed of many simple Perceptrons in a hierarchical structure forming a feedforward topology with one or more hidden layers between the input and output layers. Each layer has a different number of neurons. Figure 2 shows the basic architecture of an MLP. Since MLPs are supervised networks they require a target output to be given in order to be trained. Furthermore, with one or two hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems.

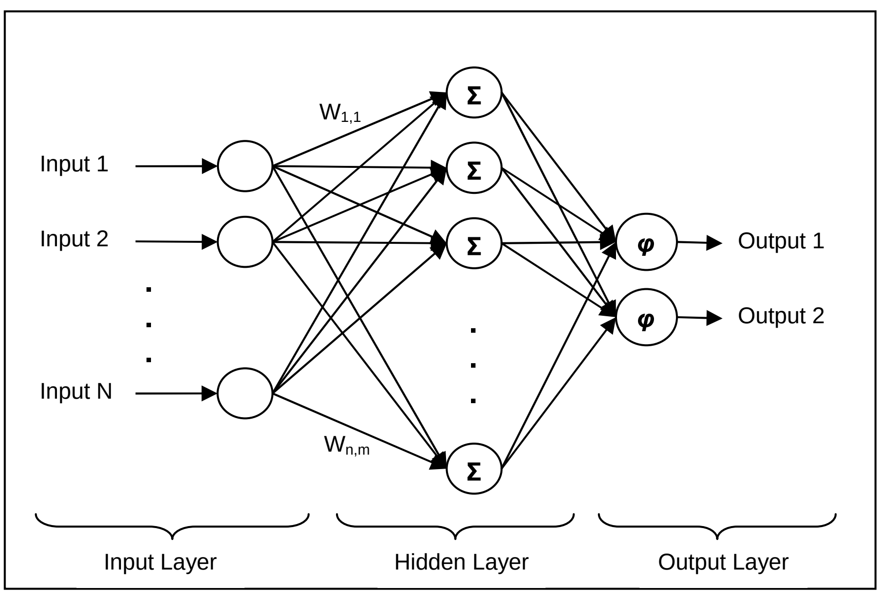


Figure 2. Multilayer Perceptron Model

MLPs can be trained using various learning algorithms, the most common being the Delta Rule and Back Propagation algorithms. The Back Propagation algorithm was devised in 1974 by Paul Werbos (Werbos, 1994) and rediscovered independently by Parker in 1985 (Parker, 1985) and Rumelhart (Rumelhart et al., 1986). Since its rediscovery, the algorithm has been widely used as a learning algorithm in feedforward networks (Kartalopoulos, 1996) in order to learn a distributed associative map between the input and output layers. The basic idea is to calculate the percentage of the total error that corresponds to the weights of each neuron. In this way, it is possible to calculate the correction for the weights of each neuron separately. However, this can be extremely complicated inside hidden layers since the output of a neuron can form the input of many other neurons. In the algorithm, the error of each neuron of the output layer is calculated individually, and these errors are then used to calculate the error of the output layer as a whole. After this, the same set of calculations takes place recursively in a backward direction (hence the name Back Propagation), until the input layer is reached. The errors calculated are then used to update the weights at each neuron. This process repeats until the error reaches an acceptable (low) level (Vlachavas et al., 2002) or when the network has iterated for a maximum number of epochs.

Appendix II: Error measurement

The error measures used for evaluating the training and testing set of data are the following: The Correlation Coefficient (CC), the Root Mean Squared Error (RMSE), the Normalised Root Mean Squared Error (NRMSE), the Mean Relative Error (MRE), the Mean Square Error (MSE), and the Mean Absolute Error (MAE).

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

where,

$$\mathrm{RMSE(n)} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left[\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \mathrm{x}_{\mathrm{act}}(\mathrm{i})\right]^{2}} \qquad \text{(App. II.2)}$$

$$\mathrm{CC} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}\left[\left(\mathrm{x}_{\mathrm{act}}(\mathrm{i}) - \overline{\mathrm{x}}_{\mathrm{act,n}}\right)\left(\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \overline{\mathrm{x}}_{\mathrm{pred,n}}\right)\right]}{\sqrt{\left[\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(\mathrm{x}_{\mathrm{act}}(\mathrm{i}) - \overline{\mathrm{x}}_{\mathrm{act,n}}\right)^{2}\right]\left[\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \overline{\mathrm{x}}_{\mathrm{pred,n}}\right)^{2}\right]}} \qquad \text{(App. II.3)}$$

$$\mathrm{MMRE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left|\frac{\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \mathrm{x}_{\mathrm{act}}(\mathrm{i})}{\mathrm{x}_{\mathrm{act}}(\mathrm{i})}\right| \qquad \text{(App. II.4)}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left|\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \mathrm{x}_{\mathrm{act}}(\mathrm{i})\right| \qquad \text{(App. II.5)}$$

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}(\mathrm{x}_{\mathrm{pred}}(\mathrm{i}) - \mathrm{x}_{\mathrm{act}}(\mathrm{i}))^{2} \qquad \text{(App. II.6)}$$

where $x_{act}(i)$ and $x_{pred}(i)$ the actual and predicted value when pattern i is presented, with i=1..n, $\overline{x}_{act,n}$, $\overline{x}_{pred,n}$ the mean value of actual and predicted samples of length n and n is the total number of patterns.

The CC measures the ability of the predicted samples to follow the upward or downward jumps in 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 an 180^{o} rotation about the time-axis. When the original series moves up, the forecasting series moves down at the same time-period and vice versa. The NRMSE is used to assess the quality of the forecasts by comparing them with those relying on the mean of the last n observations, while the MMRE, being scale and unit independent, shows the accuracy of predictions in percentage terms expressing it in a stricter way since it focuses on the sample being predicted. Thus, we are able to estimate prediction error as a fraction of the actual value, this making the MMRE the most objective error measure compared to the others used in this paper. The MSE, finally, 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.

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