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Analysis of the Current Account Balance in the Turkish Economy with NARX: A Non-linear Approach

Türk Ekonomisinde Cari İşlemler Dengesinin NARX ile Analizi: Doğrusal Olmayan Bir Yaklaşım

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ÖZ

Bu makale Türk ekonomisinde cari işlemler dengesini parametrik olmayan bir analiz yöntemiyle analiz etmektedir. Bu amaçla, Türk ekonomisinde cari işlemler dengesinin analizi için makro ekonomiye önemli oranda nüfus eden çoklu bir bağımsız değişken seti kullanmaktadır. Analizde güçlü ve doğrusal olmayan bir istatistiksel yöntem olan NARX Yapay Sinir Ağı kullanılmıştır. Analiz sonuçları, literatür araştırması sonrasında seçilen çoklu bir değişken setinin cari işlemler dengesini yaklaşık %90'ın üzerinde açıklayabildiğini ortaya koymaktadır. Bu amprik bulgu cari işlemler dengesinin karmaşık ve çoklu bir makro ekonomik değişken seti ile istatistiksel olarak güçlü bir şekilde ilişkili olduğunu göstermektedir. Bu sonuca dayanarak, bu makale cari işlemler dengesi verisini Türk ekonomi politikasında önemli bir makro ekonomik performans göstergesi olarak baz alınmasını önermektedir.

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ABSTRACT

This paper analyzes the current account balance in the Turkish economy with a non-parametric analysis method. For this purpose, it applies a multiple set of independent variables that have a significant impact on the macroeconomy for the analysis of the current account balance in the Turkish economy. NARX Artificial Neural Network, which is a powerful and non-linear statistical method, is used in the analysis. The results of the analysis uncover that a multiple set of variables selected after the literature review can explain the current account balance by over 90%. This empirical finding demonstrates that the current account balance is robustly correlated with a complex and multiple set of macroeconomic variables. Based on this result, this study proposes to employ the current account balance data as a crucial macroeconomic performance indicator in Turkish economic policy.

JEL Classifications: C45, E12, E20, E40.

1. INTRODUCTION

Current account imbalances have incremented in the global economic system since commercial and financial liberalization movements strengthened. The current account balance (CAB), associated with the net savings balance, affects the quality of a country's financial flows (see Tosun, 2020). Countries with chronic current account deficits, which demonstrate the external balance, are defined as debtor countries. To finance the external balance, the debtor countries have to attain foreign funds from the international financial markets by bearing the interest expenses. This asymmetrical relationship leads to instability in the macroeconomy by soaring external debt. Augmenting instability becoming unsustainable and shocks in global financial markets or exacerbation of adverse conditions cause reversals in the CAB (see also Milesi and Razin, 1998). The process of reversing the CAB is accompanied by devaluation. Increasing exchange rate pressure on the local currency brings about cost inflation, reducing purchasing power and leading to loss of welfare. Consequently, the increasing current account deficit becomes unsustainable, resulting in poor economic performance. Thus, considering the CAB as a crucial economic performance indicator rolls out a meaningful economic behavior (see also Yang, 2011; Tosun, 2020).

The literature analyzing the CAB is typically based on parametric analyzes with a similar structure. However, literature studies generally tend to model the CAB with one or some variables. In addition, literature studies use heterogeneous sets of independent variables. The empirical literature modeling the CAB follows nonstandard practices. This study demonstrates that predicting the CAB statistically with one or some variables via parametric models is insufficient.

This paper statistically explains the CAB for Turkey with the NARX Artificial Neural Network, a non-parametric analysis, by employing multiple variables that penetrate the economic performance in the universe of forward and feedback algorithms. For this purpose, this paper utilizes the several significant variables that literature typically applies for the determinants of the CAB. Accordingly, the primary contributions of the study to the literature are explained as follows. (i) The CAB for Turkey is analyzed with the NARX Artificial Neural Network, a robust non-parametric statistical method, (ii) This paper exhibits that the CAB is a crucial performance determiner in the Turkish economy. The remainder of this study is organized as follows. Section 2 reviews theories that try to explain the CAB. In Section 3, empirical studies analyzing the determinants of the CAB are investigated. In Section 4, the CAB for Turkey is analyzed with NARX Artificial Neural Network. In Section 5, empirical findings are evaluated.

2. THEORETICAL FRAMEWORK

This section examines theories explaining the CAB. Mainstream approaches to CAB are elasticities, absorbing, monetarist, and intertemporal approaches. Before explaining the mainstream approaches, other approaches, which form the theoretical basis for the CAB, are briefly mentioned in this section.

A lot of empirical research has found a relationship between the relative fiscal balance and the current account, consistent with the twin deficit hypothesis (Phillips et al., 2013). The Ricardian equivalence, which rejects the twin deficit hypothesis, contends that countries with lower public savings experience higher private savings. Therefore, the fiscal balance is not associated with the CAB (Debelle and Farugee, 1996).

According to life cycle theory, economic agents seek to maximize utility over a lifetime. Thus, actors save during economic activity to shift some of their consumption into retirement, when they are typically lower. The demographic structure is a significant determinant of the savings rate (Debelleve Farugee, 1996). Demographic factors have an impact on investments. Rapid population growth, particularly the rapid boost in young people, has a tendency to augment the need for investment (Williamson, 1994). Since this tendency damages the savings, it adversely affects the CAB.

2.1. Elasticities Approach

The Marshall-Lerner Condition (M-L), which considers the sensitivity of the trade balance to relative price changes, is based on a conventional approach. The condition suggests that depreciating a currency improves a country's trade balance in the long term if the aggregate of the absolute values of the import and export demand-price elasticities is more than one (Mahmud et al., 2004).

The traditional view predicts that nominal devaluation will improve the trade balance. This assumption depends on a static and partial equilibrium approach to the balance of payments (BoP) known as the elasticities approach (Bickerdike, 1920; Robinson, 1947 and Metzler, 1998). The elasticities approach provides a theoretical basis for devaluation advocates. However, in practice, increases in imported inputs due to the long-run devaluation of the exchange rate bring about cost inflation. The elasticities approach overlooks supply conditions and cost changes due to devaluation and tends to ignore the income and expense effects of exchange rate changes (Thirwall, 1980).

2.2. Absorbing Approach

The absorption approach developed by Alexander (1952) emphasizes the role of income in the BoP adjustments, taking into account the change in the trade balance. The absorption approach formulates the foreign trade balance with aggregate production and expenditures by employing the national income equation developed by Keynes for open macroeconomics. According to this approach, when aggregate production exceeds aggregate expenditures, it leads to a positive trade balance. On the other hand, when aggregate expenditures exceed aggregate output, it brings about a trade deficit. Consequently, the absorption approach focuses on the change in aggregate production and expenditures for the trade balance (Seyidoğlu, 2017).

2.3. Monetary Approach

Elasticities and absorption approaches are associated with the balance of trade. Monetary flow is a stock-variable approach and deals with the BoP from monetary dimensions. According to the monetarist approach, BoP deficits are a phenomenon that can be corrected by monetary policy (Thirlwall, 1980). The monetary approach associates the money corresponding to the BoP deficit or surplus with the stock imbalance between the money supply and the surplus in the market. Surpluses in the trading and capital account represent an overflowing supply of goods and securities. An excess in the money account reflects an excessive inflow demand for money (Johnson and Frenkel, 1976). According to the monetarist approach, BoP(s) adjustment policies can be successful if they eliminate the stock imbalance between money supply and demand (Thirlwall, 1980).

2.4. Intertemporal Approach

The primary approach of the CAB is expressed by the intertemporal model introduced by Sachs (1981) and developed by Obstfeld and Rogoff (1994). It includes significant macroeconomic variables such as net foreign assets and liabilities, foreign capital flows, and consumption is a reliable guide for the optimal CAB.

The intertemporal approach extends absorption analysis to future productivity growth expectations, government spending demands, real interest rates, forward-looking calculations of private savings and investment decisions, and sometimes even government decisions. It also performs a synthesis of the absorptive and elasticities perspective by analyzing the impact of current and future prices on savings and investment, taking into account the macroeconomic determinants of relative prices (Obstfeld and Rogoff, 1996).

The model foresees the CAB owing to the future dynamic savings and investment decisions of the relevant economic units complied with rational expectations. Decisions taken based on consumption are crucial in predicting the future. The fact that the CAB depends on an optimization result means that external debt and external assets cannot be unsustainably stocked. On the other hand, it is implied that the instantaneous imbalances that arise are only the response of economic agents to alterations in their outlays or investments (Obstfeld and Rogoff, 1996). According to the intertemporal model, if the host country is more impatient in consumption than the rest of the world, there will be a downward tendency in the current account proportional to the permanent values of its economic resources. Conversely, if domestic consumption is more patient, the CAB will increase positively (Saksonovs, 2006).

2.5. Supporting the Hypothesis by Criticizing the Theoretical Framework

Elasticities, absorption, and monetarist approaches are macroeconomic-based approaches. The intertemporal approach, on the other hand, is microeconomic based. The elasticities approach is not adequately validated in practice (see Mahmud et al., 2004). The depreciation of the local currency in foreign-dependent countries causes price inflation and thus reduces competitiveness. This result reduces the confidence of countries with current account deficits in the elasticities approach in their economic policy.

The absorbing approach indirectly associates the CAB with savings. On the other hand, the monetarist approach evaluates the CAB from a monetary perspective. The intertemporal approach does not see the current account deficit as an adverse phenomenon since it can make the time profile of consumption smoother (Pawlak and Muck, 2019). Therefore, the content of the intertemporal approach is criticized in this paper. It includes crucial information about the current account deficit, competitiveness, and the structure of the macroeconomy, and it may cause unforeseen costs that absorb consumption yields in the future. Consequently, the political economy should evaluate the current account deficit as a critical performance indicator and always eliminate the current account deficit.

The current account balance provides crucial information about a country's position in financial markets. Countries with a current account surplus can be defined as creditor countries, and countries with a current account deficit can be defined as debtor countries (see Mishkin and Eakins, 2012). Countries with current account surpluses obtain derivative yields from these sources by providing resources to global financial markets. The theoretically formulated inflation increase in countries with current account surplus loses its validity since these countries offer foreign currency exceeding the balance amount to international financial markets (Tosun, 2020).

The problem is in countries with current account deficits. Countries with current account deficits borrow from international financial markets. Developing countries whose stock markets, financial markets, and foreign direct investments (inflows) are not mature enough tend to finance their current account deficit generally with hot money resources. This factor strengthens macroeconomic conditions that create risks by increasing short-term debt. Therefore, increased risk factor raises financial costs (see Mishkin and Eakins, 2012). Due to the high-risk factor, the competitiveness of countries with higher financial expenses tends to decrease relatively.

Augmenting short-term debts due to increasing risk factors and high current account deficit creates adverse effects on official reserves by increasing risk factors in macroeconomics. Decreasing reserves leave the Central Bank alone in the exchange rate stabilization policy in the future. In this case, the Central Bank loses a significant source of power in sustaining the price stability. Owing to the high current account deficit, local currency depreciating due to the foreign exchange leaving the country reduces its purchasing power and creates adverse impacts on welfare (Tosun, 2020). The interest increase applied by the countries whose reserves are depleted and exposed to devaluation to encourage foreign exchange inflows forces the supply conditions, causing the cost of living and loss of welfare. Increasing inflation and decreasing domestic production cause the weakening of the macroeconomic structure and decrease the competitiveness of the economy in the long run.

This paper unfolds sufficient reasons to consider the current account deficit as a performance indicator (see also Yang 2011, Tosun 2020). Also, to support this view, this paper references the difference in current account balance between Northern and Southern EU countries during the 2011 EU public debt crisis. During the 2011 EU crisis, Northern EU countries (Germany, Netherlands, Belgium, Denmark, and Austria) had high current account surpluses, while Southern EU countries (Greece, Ireland, Italy, Portugal and, Spain) had high current account deficits. Southern EU countries were at the center of the 2011 EU public debt crisis. An important reason for the austere effects of the 2011 EU public debt crisis in Southern EU countries is associated with the current account deficit of the less competitive Southern EU countries (see Lane 2012; Gros 2012; Hall 2012; Obstfeld 2013; Frieden and Walter, 2017).

3. LITERATURE REVIEW

3.1. Foreign Literature

Milesi and Razin (1998) investigated the CAB of 105 low- and middle-income countries with panel data analysis for the 1973-1994 period. According to the analysis outcome, the reversal of the CAB tends to occur in countries with persistent deficits, low reserves, and unfavorable trading conditions, whereas it is less likely to happen in countries with concessional borrowing and high official transfers.

Calderon et al. (2001) searched the CAB of Africa and 64 developing countries with panel data analysis for 1975-1995. The authors applied a large set of macroeconomic data containing information on savings, aid flows, and other national income variables in the analysis. Due to differences in income elasticities, domestic income growth is positively associated with the CAB. The higher effect of private savings in the African region on the CAB indicates that consumption augments in Africa are largely financed by foreign capital. The impact of public savings on the CAB in African countries is larger than in developing countries.

Chinn and Prasad (2003) investigated the CAB of 18 industrialized and 71 developing countries with cross-section and panel regression techniques for the period 1971-1995. According to the analysis outcome, the CAB is positively related to the budget balance and net foreign asset stocks. In developing countries, financial deepening measures are positively associated with the CAB. On the other hand, openness to international trade indicators was found to be adversely correlated with CAB.

Petrasek (2005) analyzed the medium-term determinants of CAB using the panel regression technique based on the intertemporal model in 129 industrialized and developing countries for the period 1991-2000. According to the outcomes of the analysis, the intertemporal model explained the current account deficit in developed countries, yet it could not explain it in developing countries. Consequently, this study claimed that developed and developing countries have different calculation models for modeling CAB.

Chinn and Ito (2006) investigated the CAB of 19 industrialized and 70 developing countries with cross-section and panel regression techniques for the 1971-2004 period. The authors searched the impact of the financial expansion on the CAB. According to the analysis outcome, the financial expansion brings about smaller CAB(s) in countries with developed financial markets, while financial expansion leads to current account surplus in East Asian countries.

Aristovnik (2007) explored the current account accounts of 17 Central and East African countries for 1971-2005 using the panel regression technique. According to the analysis outcome, oil prices, relative income, government expenditures, economic openness, and foreign direct investments were found to be the determinants of the CAB.

Ketenci and Uz (2010) searched the CAB in 8 EU countries employing the ARDL cointegration analysis technique for the period 1995-2008. According to the analysis results, the authors found evidence that private saving, investment, and real exchange rates affect the CAB.

Belke and Dreger (2011) investigated the CAB of 11 EU countries for the 1982-2008 period with the panel cointegration technique. According to the analysis result, while the effect of income is higher than the effect of the real exchange rate in countries with surplus in CAB or less deficit in CAB, the situation is the opposite in countries with a high current account deficit. In other words, the real exchange rate (competitiveness factor) is a more significant variable for countries with current account deficits.

Yang (2011) explored the CAB of 8 developing Asian countries with the cointegrated VAR methodology for 1980-2009. According to the analysis outcome, there is a cointegration relationship between NFA stock, openness to trade, real exchange rate, relative income, and CAB.

Bollano and Ibrahimaj (2015) empirically examined the determinants of the CAB for a sample of 11 Central and Eastern EU countries using the panel VAR model for the period 2005-2014. The analysis results demonstrated that GDP, fiscal balance, and real exchange rate are the primary determinants of the CAB in these countries.

Chuku et al. (2017) analyzed the CAB of 15 West African countries with the panel cointegration technique for the period 1980-2014. According to the analysis outcomes, the determinants of current account dynamics differ resting on the time period of the analysis. Real exchange rate, fiscal policy, trade openness, investment, and income levels were found to be critical determinants of the CAB in the short run.

Riaz et al. (2019) analyzed the CAB of South Asian countries with the cointegration technique developed by Johansen and Juselius for 1984-2015. According to the analysis results, net foreign assets, trade openness, domestic relative income variables were found to be more related to the CAB than the nominal exchange rate.

Pawlak and Muck (2019) empirically investigated the determinants of the CAB of 28 EU countries with the cross-section regression technique for 2008-2016. The authors determined that income, budget balance, first international investment position, dependency ratio, and fuel balance were associated with the CAB.

Aimon et al. (2020) analyzed the CAB of low- and middle-income ASEAN countries with the simultaneous equation model approach for 2000-2017. According to the analysis outcomes, while the CAB is positively affected by financial expansion, government expenditures, real GDP, and real exchange rate, it is adversely affected by foreign direct investments.

3.2. Literature for Turkey

Peker and Hotunoğlu (2009) explored the determinants of the CAB in the Turkish economy through the VAR model for 1992-2007. According to the analysis results, the real effective exchange rate index, the overnight real interest rate, and the ISE index were found to be the determinants of the CAB.

Ketenci and Uz (2010) explored the determinants of the CAB in the Turkish economy with the ARDL approach for the period 1987-2008. The authors discovered that the exchange rate affects the CAB potently.

Canıdemir (2011) investigated the determinants of the CAB in the Turkish economy with the multiple linear regression model for 1989-2010. According to the analysis findings, the overall budget deficit, the expansion in imports, and the real exchange rate expands the current account deficit, while the increment in exports and interest rates contracts the current account deficit.

Dam et al. (2012) analyzed the determinants of the CAB in the Turkish economy with the VAR approach for 2002-2011. According to the analysis findings, the CAB in Turkey is affected by foreign debt interest payments, transfer payments, and tourism expenditure shocks.

İyidogan and Erkam (2013) examined the hypothesis of twin deficits for the Turkish economy with the Granger causality test for the 1987-2005 period. According to the analysis results, there is a one-way causality relationship from CAB to budget deficits. The analysis outcomes demonstrated that the twin deficit hypothesis is not valid for the Turkish economy.

Göçer (2013) reached the following results for the CAB in the Turkish economy by using the variance decomposition for the 1996-2012 period by employing the VAR model. In the relevant period, 9% of the CAB in the Turkish economy was energy outlays, 6% foreign trade balance excluding energy, 6% foreign debt interest payments, 1.8% foreign direct investment profit transfer, 1.5% foreign portfolio investments excluding investment profit transfers and 74.95% by itself.

Benli and Tonus (2019) analyzed the determinants of the CAB in the Turkish economy by using the ARDL approach for the period 2006-2019. According to the analysis findings, the budget balance, exchange rate, and interest rate affect the CAB in the long run, while GDP and budget balance affect it in the short run.

Turan and Afsal (2020) analyzed the determinants of the CAB in the Turkish economy by employing the ARDL for 1975-2018. According to the analysis outcomes, the financial account, growth rate, oil prices, investments, and real exchange rate were found to be the determinants of the CAB.

3.3. Literature Review

In this section, the literature studies for foreign countries and Turkey, which analyze the determinants of the CAB, are evaluated together. The literature typically associates the CAB with GDP, foreign trade balance, budget balance, net foreign asset stock, foreign direct investments, real exchange rate, and the real interest rates (See Table 1). When all these variables are evaluated together, we can understand that they have a high capacity to represent a macroeconomic performance. Therefore, these are selected as the independent variables for the analysis of the CAB in Turkey.

Table 1: Literature Studies That Find A Relationship with CAB Specific to the Variable

Literature Studies	Variable
Milesi and Razin (1998), Candemir (2011), Göçer (2013)	Foreign Trade Balance (FTB)
Calderon et al. (2001), Yang (2011), Iyidogan and Erkam (2013), Ballano and Ibrahimaj (2015), Turan and Afsal (2016), Pawlak and Muck (2019), Aiomon et al. (2020)	Gross Domestic Product (GDP)
Chinn and Prasad (2003), Canidemir (2011), İyidogan and Erkam (2013);	Budget Balance (BB)
Chinn and Parasad (2003), Yang (2011), Riaz et al. (2019)	Net Foreign Asset Stock (NFA)
Aristovnik (2007), Göçer (2013), Aimon et al. (2020)	Foreign Direct Investment (FDI)
Ketenci and Uz (2010), Yang (2011), Belke and Dreger (2011), Ballano and Ibrahimaj (2015), Turan and Afsal (2016), Chuku et al. (2017)	Real Exchange Rate (RER)
Peter and Hotunoğlu (2009), Canıdemir (2011), Dam et al. (2012), Göçer (2013), Benli and Tonus (2019)	The Real Interest Rate (RIR)

4. EMPIRICAL ANALYSIS

4.1. Hypothesis

This paper questions whether the CAB can be considered as a crucial performance determiner for Turkish economy. The hypothesis of this study is formulated as follows. H_1: The CAB for Turkey is statistically explained with a multiple set of independent variables representing economic performance. Obtaining the findings confirming the hypothesis will support the evaluation of the CAB as a critical macro-economic performance determiner.

4.2. Reasons for Choosing a Nonparametric Method

The important reasons for selecting a nonlinear method in this study are explained as follows: (i) There are multicollinearity problem between the independent variables that have been verified in theory. (ii) GDP, BB, NFA, and FDI series are not normally distributed (see Table 2).

Table 2: Jarque-Bera Normality Test Results

Desc. Statistics	CAB	BB	FTB	FDI	GDP	NFA	RER	RIR
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	-0.05	0.33	0.09	-0.28	-0.29	-0.54	0.19	-0.34
Max	2.74	1.39	2.42	3.70	2.91	2.82	1.59	2.70
Min	-2.83	-4.36	-2.33	-1.76	-1.15	-0.77	-2.26	-1.59
Std. Dev.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Skewness	0.33	-1.74	0.02	1.34	1.01	1.35	-0.71	0.72
Kurtosis	3.49	7.69	2.71	5.52	3.23	3.41	2.65	2.52
Jarque-Bera	1.76	85.79	0.20	3.13	10.34	18.72	5.42	5.76
Prob.(*)	0.41	0.00	0.90	0.00	0.00	0.00	0.06	0.05

Note: (*) symbolizes that the decision is made with a 5% margin of error.

(iii) The stationarity order (SO) of the variables is different from each other. According to Augmented Dickey-Fuller (ADF) stationary test, which based on SIC information criteria with 5% margin of error, FDI at the level, CAB, BB, FTB, REER, and RIR at the first difference, and GDP and NFA become stationary at the second difference (see Table 3).

Table 3: ADF Stationary Test Results

SO	FDI		CAB		BB		FTB	
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
I(0)	-5.202	0.0001	-2.281	0.1814	1.646	0.9995	-2.533	0.1129
	-6.241	0.0000	-2.718	0.2335	0.361	0.9985	-2.653	0.2594
I(1)			-4.627	0.0004	-14.084	0.0000	-4.795	0.0002
			-4.623	0.0025	-14.649	0.0000	-4.857	0.0013
SO	**REER**		**RIR**		**GDP**		**NFA**	
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
I(0)	-0.682	0.842	-2.159	0.222	9.196	1.000	1.721	0.9996
	-2.69	0.240	-2.386	0.382	2.192	1.000	1.459	1.000
I(1)	-9.170	0.000	-6.612	0.000	0.0993	0.962	-0.651	0.8489
	-9.466	0.000	-6.557	0.000	-15.743	0.000	-3.065	0.1259
I(2)					-8.285	0.000	-4.039	0.0027
					-8.294	0.000	-3.949	0.0173

4.3. Analysis Methodology

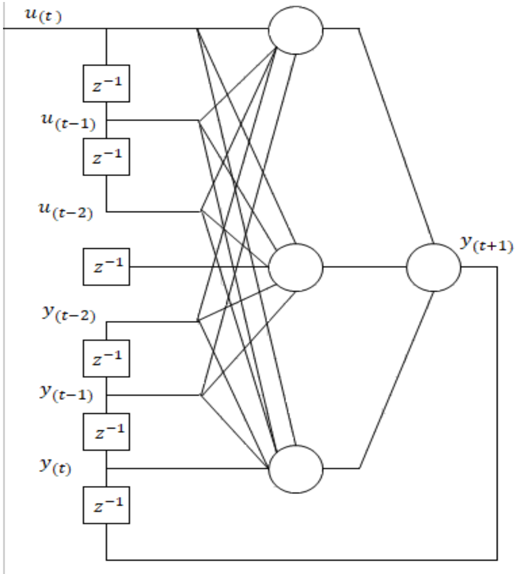
In the study, (I) the series are first normalized. (ii) Since there are negative values in the data, normalization is made according to the Z-score. (iii) After the series are normalized, the parameters of the NARX Artificial Neural Network are determined. (iv) NARX Artificial Neural Network is created after the parameters are determined. (v) Next, the training of the network is started. (vi) The network is trained according to the least-squares error technique and the highest performance.

4.4. NARX Analysis Method

Nonlinear Autoregressive with External Input (NARX) is a multi-layered back and forward feed-forward dynamic artificial neural network with hidden layer/or layers. The independent variable (x) in NARX is considered an exogenous variable. Exogenous variable refers to the inclusion of external factors in the model for the solution of the problem.

Learning in NARX networks is more effective than other neural networks (see Figure 1). Gradient descent in NARX produces more excellent outcomes, networks converge more quickly, and generalize more perfectly than other networks (Lin et al., 1996; Gao and Er, 2005; Diaconescu, 2,008). NARX can also be employed efficiently in nonstationary and nonlinear time series (see Chaudhuri and Ghosh, 2016).

Figure 1: Non-linear Autoregressive with External Inputs NARX. Source: Chaudhuri and Ghosh, 2016.



NARX is an iterative neural network that offers a multi-layer (MLP) perception-based delay module (Tapped Delay Lines) and feedback (Yu et al., 2019). NARX, whose mathematical representation is denoted in equation 1, is a dynamic neural network widely employed for input-output modeling of nonlinear dynamic systems.

$$\bar{y} = f[u(t-1),\dots u(t-du), y(t-1)\dots y(t-dy)] \tag{1}$$

$$(in\ vector\ form \rightarrow y(n+1) = f[y(n); u(n)])$$

At time (t), $u(t) \in R$ and $y(t) \in R$ represent input and output, and (du) and (dy) represent embedded input and output memory, respectively. (f) denotes the function presenting the behavior of the system modeled non-linearly (Lobo et al., 2014). Dynamic neural networks contain time delay lines employed for non-linear filtering and forecast.

Functional values of (g), $g{:}\,R^m \rightarrow R$ produce the observed sample pattern pairs $(x_1,y_1),(x_2,y_2)$. The sample data alters the parameters in the neural predictor and approximates the nervous system input-output responses to the input-output responses of the unknown predictor (g). This is similar to learning from nervous system experience in brain anatomy. In the NARX model, it is expected that equation 2 equals 0 and (e_t) has a finite variance (σ^2) (Allende et al., 2002):

$$E(e_t)|x_{t-1,}x_{t-2,}x_{t-3}\dots\dots..x_{t-\alpha}| \tag{2}$$

(α) denotes the optimal delay number. Under these conditions, the optimal estimator of the Mean Square Errors (MSE) is shown in equation 3 (Diaconescu, 2008):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i)^2 \tag{3}$$

As shown in equation 4, a NARX model is a multiple feed-forward (MLFFN) ANN model. Here, $(w^{|1|})$ is the calculated weight between the input and the hidden layer, and $(w^{|2|})$ is the calculated weight between the hidden layer and the output (Allende et al., 2002).

$$g_\alpha(x,w) = \tau_2[\sum_{j=1}^{\alpha} w_j^{|2|}\, \tau_1(\sum_{i=1}^{m} w_{ij}^{|1|}\, x_i + w_{\alpha+1,j}^{|1|}) + w_{\alpha+1}^{|2|}] \quad (4)$$

A feed-forward Artificial Neural Network supplies a nonlinear approximation to (v) given by

$$\hat{x_t} = \hat{v}(x_{t-1}, x_{t-2}, x_{t-3} \dots \dots x_{t-s}) = \sum_{j=1}^{\alpha} w_j^{|2|}\, \tau_1[\sum_{i=1}^{s} w_{ij}^{|1|}\, x_{t-i} + w_{s+1,j}^{|1|}] \quad (5)$$

where the function (τ_1) is a smooth bounded monotic function (Allende et al., 2002). (s) and (t) indicate the time delay parameter. Equations (4) and (5) are similar to each other. (τ_1) exhibits the activation function belonging to the hidden layer, which has a sigmoid function shown in equation 6, and (τ_2) denotes the linear function in the output layer.

$$f(x) = \frac{1}{1+e^{-x}} \quad (6)$$

The hidden layer is a hidden node formulated with the sigmoidal functions. The output layer is a node with a linear transfer function (Diaconescu, 2008). The output node has no bias. The parameters $(w_j^{|1|})$ *and* $(w_{ij}^{|2|})$ are estimated by training, and $(\hat{v})$ is the estimator of (v).

The estimate is attained by converging to the local minimum, similar to equation (7). Here, (T) is the number of free parameters determined by the network topology. $(L_{(n)})$ is the function employed to obtain MSE values according to parameters. $(\hat{w})$ is the predictable parameter (Allende et al., 2002):

$$\widehat{w} = arg, min\{L_{(n)}(w): w \in W\}, W\underline{C}R^T \quad (7)$$

This approach is performed by Gradient Descent known as super self-adaptive ''*backpropagation*'' or quadratic method for learning. According to the weight parameter, the MSE function (the loss function) is shown in equation 8. Equation 8 demonstrates the measure of the accuracy of the topology of the network. The primary objective of the ANN model is to converge this equation iteratively to the minimum.

$$L_n(w) = \frac{1}{n}\sum_{i=1}^{n}[(y_i - g_\alpha(x_i, w)^2] \quad (8)$$

NARX has feedback and memory functions. The output of each moment is rested on a comprehensive dynamic synthesis of the system before the current moment (Yu et al., 2019). The structure of the feedback network is implemented in two different ways as Series-Parallel (SP) and Parallel (P) mode. Backpropagation in training the NARX network takes place in one of the two respective modes.

As shown in equation 9, in SP mode, the regressor of the output consists only of the values of the system output (Menezes and Barretuilharme, 2008):

$$\hat{y}(n+1) = f[y_{sp}(n); u(n)] = f[y(n) \dots y(n-dy+1), u(n), u(n-1) \dots . u(n-du+1)] \quad (9)$$

The caret (^) symbol is used to indicate predictive values. (y) output, (u) input, (du) and (dy) indicate embedded input and output memory.

In the P mode shown in equation 10, the estimated outputs are the feedback, and the regressor of the output is included (Menezes and Barretuilharme, 2008):

$$\hat{y}(n+1) = \hat{f}[y_p(n); u(n)] = \hat{f}\begin{bmatrix}\hat{y}(n) \dots \hat{y}(n-dy+1), u(n), u(n-1) \\ \dots u(n-du+1)\end{bmatrix} \quad (10)$$

In NARX implementation, the output-memory order typically formulated $(dy) = 0$, thus diminishing the NARX network to the TDNN architecture, namely:

$$y(n+1) = f[u(n)] = f[u(n), u(n-1) \dots . u(n-du+1)] \quad (11)$$

where $u(n) \in R^{du}$ is the input regressor.

4.5. Selecting the Training Algorithm

In this study, training is performed by the Levenberg-Marquardt (LM) backpropagation algorithm. The LM is a an iterative and adaptive technique that finds the minimum values of a multivariate function. This minimum is derived as the sum of squares of non-linear real-valued functions (Marquardt, 1963). In the estimation process, when model parameters are not close to their optimal values, the Levenberg-Marquardt algorithm acts in a highly convergent gradient-descent way by updating parameter values in the direction opposite to the gradient of the objective function. In other cases, when parameters are close to their optimal values, the Levenberg-Marquardt algorithm starts acting as the Gauss-Newton method, assuming that the objective multivariate function is quadratic in parameters near their optimal solutions (Marquardt, 1963, cited by Matkovskyy et al., 2015).

Backpropagation algorithms using first-order derivatives have low training efficiency. In addition, their convergence rates and performance are insufficient (Ferrari and Jensenius, 2008). Using LM quadratic derivative derived from Steep Descent and Newton algorithms significantly increases learning speed and performance (Wilamowski and Chen, 1999).

The LM algorithm upgraded by Donald Marquardt in 1963 is shown below (Gavin, 2020): (λ) values are normalized to the Hessian (h) fit criterion of Chi-square $(j^T wj)$. Here, (y) represents the real value of the dependent variable, $(\hat{y})$ the predictive value of the dependent variable, $(j) \rightarrow (pxm)xn$ size Jacobian matrix (p represents the training sample number, m the output number, n the number of weights), (T) transpose, (λ) denotes Marquardt damping parameter, (w) weight parameter, (h) deviation.

$$[j^T wj + \lambda_{diag}(j^T wj)]h_{LM} \quad (12)$$

$$j^T wj(y - \hat{y}) \tag{13}$$

The LM algorithm adaptively switches parameter updates between Gradient-Descent and Gauss-Newton. The damping parameter is initialized large at the Steep Descent step. If the iteration results in a bad approximation in the steep descent step, the damping parameter is increased; in other words, the Gradient-Descent algorithm shown in equation 14 is applied.

$$X_{k+1} = X_k - \lambda \nabla f(X_k) \tag{14}$$

On the contrary, if the iteration results in a good convergence, the Gauss-Newton algorithm shown in equation 15 is employed.

$$X_{k+1} = X_k - [hf(X_k)]^{-1} \nabla f(X_k) \tag{15}$$

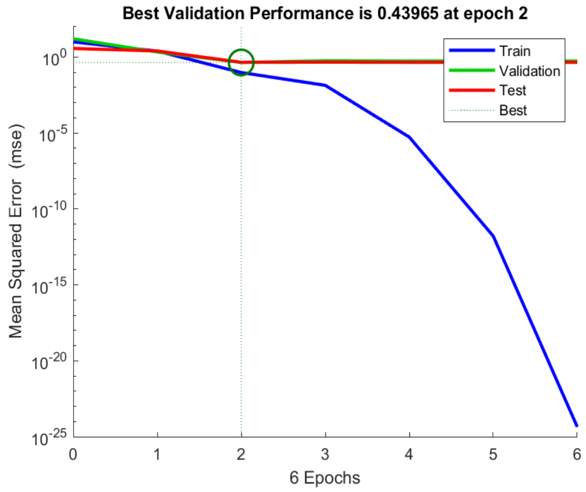
4.6. Testing the Hypothesis

For some variables, data for the period "before 2006" and "after 2020" could not be found. Therefore, the period between 2006-2020 is selected as the research period. The data is quarterly and obtained from the digital database of the Turkish Central Bank. In this study, the models are applied with the help of the MATLAB® R2021b program.

Making an optimal decision is crucial for the structural parameters when constructing an optimal NARX model. The structural parameters of the NARX model are the number of hidden layers, the number of neurons in the hidden layer, and the number of input layer delays (Yu et al., 2019). According to the theory, one hidden layer should be selected for more effective results. Choosing more than one hidden layer leads to ineffective results (see Maters, 1993). Therefore, this paper employs one hidden layer. 70% of the data is partitioned for training, 15% for validation, and the remaining 15% for testing. The number of neurons is selected as "20" in accordance with the parameters. In the NARX analysis, *"two lags"* are applied for the lagged values of the dependent variable.

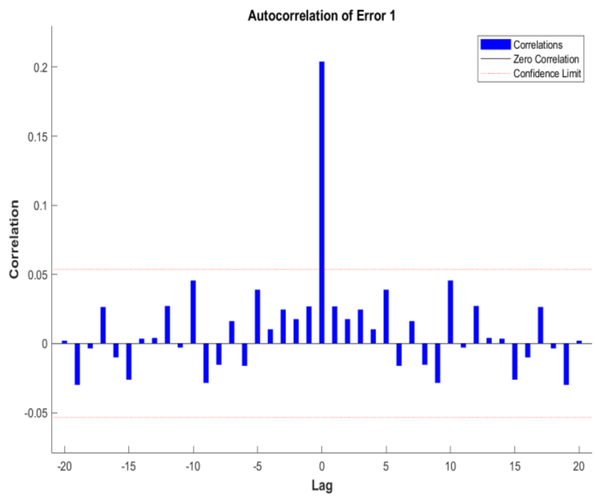
In the tests, training performance is measured by minimum MSE values. Since NARX is an autoregressive model, there should be no autocorrelation problems in the model. Therefore, minimum MSE values are evaluated together with autocorrelation in the analysis. In addition, test, training, and validation regression values should be successfully converged to each other. These conditions are evaluated together in this study.

Figure 2: Mean Square Error Performance of the Model.



As a result of the analysis, the optimum result is obtained in the 6th iteration. The best validation performance is achieved in the 2nd iteration with 0.43965 (see Figure 2).

Figure 3: Autocorrelation of Error.



The autocorrelation outcomes of the model are shown in Figure 2. In the figure, the blue bars are between the confidence limit. It means that all the correlations are under the confidence limit (see Figure 3).

Table 4: Regression Results

Input: Double array of 60-time steps with 7 features			
Output: Double array of 60-time steps with 1 feature			
Algorithm			
Data division: Random			
Training algorithm: Levenberg-Marquardt			
Performance: Mean Squared Error			
Training outcomes			
Layer size:	20		
Time delay:	2		
	Observations	**MSE**	**R**
Training	40	0,0956	0,9511
Validation	9	0,4396	0,9321
Test	9	0,4504	0,8606
(*) Train a neural network to forecast series y(t) past values of y(t) and past values of another series x(t).			

Training, validation, and test regression results confirm an explanation rate of over 90%. According to these outcomes, the independent variables can statistically explain the CAB with a performance of over 90%. Consequently, results supporting the H_1 hypothesis are obtained (see Table 4).

CONCLUSION

The literature generally tends to model the CAB with one or some variables by parametric analysis (see Sections 2.2 and 2.3). Analyzing the CAB by associating it with several variables may be meaningful in order to make some predictions. However, this approach is not sufficient for the CAB. The CAB should be explained with a multiple set of variables that penetrate the macroeconomy.

Parametric models have multicollinearity problems. They also include assumptions such as stationarity and normal distribution. Therefore, NARX artificial neural network, which is a powerful nonlinear statistical method, is employed in this paper. The results of the empirical analysis demonstrate that a multiple set of variables (GDP, foreign direct investments, foreign trade balance, budget balance, net foreign assets, real exchange rate, and the real interest rate) can explain the current account balance by over 90%. This result supports the hypothesis (H_1) that the CAB can be considered a crucial performance indicator in the Turkish economy (see also Yang 2011; Tosun 2020) (see also Lane 2012; Gros 2012; Hall 2012; Obstfeld 2013; Frieden and Walter 2017 for North and South EU countries). Based on this finding, this paper offers the Turkish political-economic system to use the current account balance data as a performance indicator.

REFERENCES

Alexander, S.S. (1952). "Effects of A Devaluation on a Trade Balance", International Monetary Fund Staff Papers, 2, 263–278.

Aimon, H., Kurniadi A.P., and Sentosa S.U. (2020). "Determinants and Causality of Current Account Balance and Foreign Direct Investment: Lower Middle Income Countries in ASEAN" in 3rd International Research Conference on Economics and Business, KnE Social Sciences, 10-22. DOI 10.18502/kss.v4i7.6839.

Allende, H., Moraga C., and Salas, R. (2002). Artificial Neural Networks in Time Series Forecasting: A Comparative Analysis", Kybernetika, 38(6), 685-707.

Aristovnik, A. (2007). ''Short and Medium Term Determinants of Current Account Balances in Middle East and North Africa Countries'', William Davidson Institute Working Paper, No. 862.

Belke, A. and Dreger C. (2011). ''Current Account Imbalances in the Euro Area: Catching Up or Competitiveness?'', German Institute for Economic Reserachi, No. 1106.

Benli, A., and Tonus Ö. (2019). "Türkiye Ekonomisinde Cari İşlemler Açığının Belirleyicileri: Dönemler Arası Yaklaşım", Anadolu Üniversitesi Sosyal Bilimler Üniversitesi, 19(3), 437-460.

Bickerdike, C.F. (1920). "The Instability of Foreign Exchange," Economic Journal, 30, 118-122.

Bollano, J., and Ibrahimaj D. (2015). " Current Account Determinants in Central Eastern European Countries", Graduate Institute Geneva Working Paper, No. HEIDWP0022-2015.

Calderon, C., Chong C., and Loayza N. (2001). "Are African Current Account Deficits Different? Stylized Facts, Transitory Shocks, and Decomposition Analysis", World Bank Working Paper Series, No. WP/01/04.

Canıdemir, S., Uslu R., Ekici D., and Yarat M. (2011). "Türkiye'de Cari Açığın Yapısal ve Dönemsel Belirleyicileri", Ekonomik Yaklaşım Kongreler Dizisi VII Gazi Üniversiyesi Ankara.

Chinn, M.D., and Ito H. (2003). "Current Account Balances, Financial Development and Institutions: Assaying the World "Saving Glut", Sorthcoming in the Journal of International Finance and Money.

Chinn, M.D., and Prasad E.S. (2003). "Medium-term Determinants of Current Accounts in Industrial and Developing Countries: An Empirical Exploration", Journal of International Economics, 59, 47-76.

Chaudhuri, T.D., and Ghosh I. (2016). "Artificial Neural Network and Time Series Modeling Based Approach to Forecasting the Exchange Rate in A Multivariate Framework. Journal of Insurance and Financial Management, 1(5), 92-123.

Chuku, C., Atan J., Obioesio F., and Onye K. (2017). "Current Account Adjustments and Integration in West Africa", African Development Bank Group Working Paper Series, No. 287.

Dam, M.M., Göçer İ., Bulut Ş., and Mercan M. (2012). "Determinants of Turkey Current Account Deficit: An Econometric Analysis", 3rd International Symposium on Sustainable Development, Sarajevo; 111–122.

Debelle, G., and Farugee H. (1996). ''What Determines the Current Account?'', IMF Working Paper, No. 058.

Diaconescu, E. (2008). "The Use of NARX Neural Networks to Predict Chaotic Time Series" WSEAS Transactions on Computer Research, 3(3), 182-191.

Frenkel, J.A., and Johnson H.G. (eds) (1976). "The Monetary Approach to the Balance of Payments", London: Allen and Unwin.

Frieden, J.A., Walter S. (2017). "Understanding the Political Economy of the Eurozone Crisis. The Annual Review of Political Science, 20, 371-390.

Gao, Y.E., and Meng J. (2005). "NARMAX Time Series Model Prediction: Feedforward and Recurrent Fuzzy Neural Network Approach", Fuzzy Sets and Systems, 150(2), 331-350.

Gavin P. H. (2020), ''The Levenberg-Marquardt Algorithm for Nonlinear Least Squares Curve-Fitting Problems'', Department of Civil and Environmental Engineering Duke University.
https://people.duke.edu/~hpgavin/ce281/lm.pdf
(Acessed on 28 February 2022).

Gros, D. (2012). "Macroeconomic Imbalances in the Euro Area: Symptom or Cause of the Crisis?" CEPS Policy Briefs Centre for European Policy Studies, No. 266.

Göçer, İ. (2013). ''Türkiye'de Cari Açığın Nedenleri, Finansman Kalitesi ve Sürdürülebilirliği: Ekonometrik Bir Analiz'', Eskişehir Osmangazi Üniversitesi İİBF Dergisi, 8(1), 213-242.

Hall, P.A. (2012). "The Economics and Politics of the Euro Crisis. German Politics, 21(4), 355-371.

İyidoğan, P.V., and Erkam S. (2013). ''İkiz Açıklar Hipotezi: Türkiye için Amprik Bir İnceleme (1987-2005)'', Pamukkale Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 15(2013), 39-48.

Ketenci, N., and Uz I. (2010). "Determinants of Current Account in the EU: The Relation Between Internal and External Balances in the New Members", MRPA Working Paper, No.27466.

Lane, P.R. (2012). "The European Sovereign Debt Crisis". Journal of Economic Perspectives, 26(3), 49-68.

Lin, T., Horne B.G., Tino P., and Giles L.C. (1996). "Learning Long-term Dependencies in NARX Recurrent Neural Networks. IEEE Transactions on Neural Network, 7(6), 1329-1351.

Lobo, A.L.M., Osorio G.A., Yau L.J.R., Cisnero O.S., Moreno P. (2014). "A Digital Predistortion Technique Based on a NARX Network to Linearize Gan Class F Power Amplifiers. *2014 IEEE 57th International Midwest Symposium on Circuits and Systems (MWSCAS)*. DOI: 10.1109/MWSCAS.2014.6908515.

Marquardt, D. (1963). "An Algorithm for Least-Squares Estimation of Nonlinear Parameters". SIAM Journal on Applied Mathematics, 11, 431-441.

Mahmud, S.F., Ullah A., and Yücel E.M. (2004). "Testing Marshall-Lerner Condition: A Non-parametric Approach", Applied Economics Letters, 11, 231-236.

Masters, T. (1993). "Practical Neural Network Recipes in C++", Toronto: Academic Press.

Matkovskyy, R., Bouraovi T., Hammami H. (2015). "Estimation and Prediction of an Index of Financial Safety of Tunisia". MPRA Paper No, 74573.

Menezes, J.M.P., and Barretuilharme A. (2008). Long-term Time Series Prediction with the NARX Network: An Empirical Evaluation. Neurocomputing, 71(16-18), 3335-3343.

Metzler, L. (1948). "A Survey of Contemporary Economics", Vol. I, Homewood: IL Richard D. Irwin.

Milesi, G.M. and Razin F.A. (1998). ''Current Account Reversals and Currency Crises: Empirical Regularities'', IMF Working Paper, No. WP/98/89.

Mishkin, F.S., and Eakins S. (2012). Financial Markets and Institutions. 7th edition. The USA: Pearson.

Obstfeld, M., and Rogoff K. (1994). "The Intertemporal Approach to the Current Account", NBER Working Paper Series, No. 4893.

Obstfeld, M., and Rogoff K. (1996). "Foundations of International Macroeconomics", Cambridge: MIT Press MA.

Obstfeld, M. (2013). "Some Lessons of the Euro Crisis. European Commission Economic Papers", No. 493.

Pawlak, K.K., and Muck J. (2019). "Structural Current Account Benchmarks for the European Union Countries: Cross-section Exploration", NBP Working Paper, No. 320.

Peker, O., and Hotunluoğlu H. (2009). "Türkiye'de Cari Açığın Nedenlerinin Ekonometrik Analizi", Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi, 23(3), 221-237.

Petrasek, L. (2005). "The Determinants of Current Account Dynamics in the Medium Run: An International Approach",https://corescholar.libraries.wright.edu/econ_student/40 (Accessed on 28, February 2022).

Phillips, S., Catão L., Ricci L., Bems R., Das M., Di Gionanni J., Unsal D.F., Castillo M., Lee J., Rodriguez J., Vargas M. (2013). "The External Balance Assessment (EBA)

Methodology. International Monetary Fund Working Paper, No. 13/272.

Riaz, F., Javid A.Y., and Mubarik F. (2019). "Macroeconomic Determinants of Current Account in South-Asian Countries." Paradigms, 13(1), 106-112.

Robinson, J. (1947). “The Foreign Exchanges”, Essays in the Theory of Employment, Oxford: Basil Blackwell.

Sachs, J.D. (1981). “The Current Account and Macroeconomic Adjustment in the 1970s”, Brookings Papers on Economic Activity, 201-268. https://doi.org/10.2307/2534399.

Saksonovs, S. (2006). ‘’The Intertemporal Approach to the Current Account and Currency Crises’’, Cambridge University United Kingdom CB3 9EU Darwin College Research Report, No. DCRR-005.

Seyidoğlu, H. (2017). ‘’Uluslararası İktisat’’, İstanbul: Güzemcan Yayınları.

Thirlwall, A.P. (1980). ‘’The Absorption Approach to the Balance of Payments. In: Balance-of-Payments Theory and the United Kingdom Experience’’, London: Palgrave.

Tosun, T.T. (2020). “Türk Ekonomisinde Cari İşlemler Hesabının Belirleyicilerinin Yapay Sinir Ağı ile Analizi”, İstanbul Ticaret Üniversitesi Working Paper Series, No. 248.

Turan, T., and Afsal M.Ş. (2020). “Türkiye’de Cari Açığın Belirleyicileri: Amprik Bir Analiz”, Finans Politik & Ekonomik Yorumlar, 651, 217-236.

Williamson, J. (1994). “Estimates of FEERs. [in:] J. Williamson (ed.), Estimating Equilibrium Exchange Rates”, Washington: Institute for International Economics.

Wilamowski, B.M., Chen Y. (1999). “Efficient Algorithm for Training Neural Networks with One Hidden Layer. In Proc. of the International Joint Conference on Neural Networks, 3, 1725-1728.

Yang, L. (2011). ‘’An Empirical Analysis of Currrent Account Determinants in Emerging Asian Economies’’, Cardiff Economics Working Papers, No. E2011/10.

Yu, X., Zhuang C., and Longxing Q. (2019). “Comparative Study of SARIMA and NARX Models in Predicting the Incidence of Schistosomiasis in China”, Mathematical Biosciences and Engineering, 16(4), 2266-2276.

Annex-1: Advanced Script and Employed Functions

Advanced Script

```
% Solve an Autoregression Problem with External Input with a NARX Neural Network
% Script generated by Neural Time Series app
% Created 24-Feb-2022 22:03:17
% This script assumes these variables are defined:
%   input - input time series.
%   output - feedback time series.
X = tonndata(input,false,false);
T = tonndata(output,false,false);
% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
% Create a Nonlinear Autoregressive Network with External Input
inputDelays = 1:2;
feedbackDelays = 1:2;
hiddenLayerSize = 20;
net = narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn);
% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback output
% For a list of all processing functions type: help nnprocess
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};
% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular network,
% shifting time by the minimum amount to fill input states and layer
% states. Using PREPARETS allows you to keep your original time series data
% unchanged, while easily customizing it for networks with differing
% numbers of delays, with open loop or closed loop feedback modes.
[x,xi,ai,t] = preparets(net,X,{},T);
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'time'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

```
% Choose a Performance Function
% For a list of all performance functions type: help
nnperformance
net.performFcn = 'mse'; % Mean Squared Error
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate', 'ploterrhist',
   'plotregression', 'plotresponse', 'ploterrcorr',
'plotinerrcorr'};
% Train the Network
[net,tr] = train(net,x,t,xi,ai);
% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)
% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotresponse(t,y)
%figure, ploterrcorr(e)
%figure, plotinerrcorr(x,e)
% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input
with a direct
% connection from the output layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
view(netc)
[xc,xic,aic,tc] = preparets(netc,X,{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(net,tc,yc)
% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop
form for as
% long as there is known output data, and then switch to
closed-loop form
% to perform multistep prediction while providing only the
external input.
% Here all but 5 timesteps of the input series and target
series are used
% to simulate the network in open-loop form, taking
advantage of the higher
% accuracy that providing the target series produces:
numTimesteps = size(x,2);
knownOutputTimesteps = 1:(numTimesteps-5);
predictOutputTimesteps = (numTimesteps-
4):numTimesteps;
X1 = X(:,knownOutputTimesteps);
T1 = T(:,knownOutputTimesteps);
[x1,xio,aio] = preparets(net,X1,{},T1);
[y1,xfo,afo] = net(x1,xio,aio);
% Next the the network and its final states will be converted
to
% closed-loop form to make five predictions with only the
five inputs
% provided.
x2 = X(1,predictOutputTimesteps);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(x2,xic,aic);
multiStepPerformance =
perform(net,T(1,predictOutputTimesteps),y2)
% Alternate predictions can be made for different values of
x2, or further
% predictions can be made by continuing simulation with
additional external
% inputs and the last closed-loop states xfc and afc.
% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a
timestep early.
% The original network returns predicted y(t+1) at the same
time it is
% given y(t+1). For some applications such as decision
making, it would
% help to have predicted y(t+1) once y(t) is available, but
before the
% actual y(t+1) occurs. The network can be made to return
its output a
% timestep early by removing one delay so that its minimal
tap delay is now
% 0 instead of 1. The new network returns the same outputs
as the original
% network, but outputs are shifted left one timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
view(nets)
[xs,xis,ais,ts] = preparets(nets,X,{},T);
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)
% Deployment
% Change the (false) values to (true) to enable the following
code blocks.
% See the help for each generation function for more
information.
if (false)
   % Generate MATLAB function for neural network for
application
   % deployment in MATLAB scripts or with MATLAB
Compiler and Builder
   % tools, or simply to examine the calculations your
trained neural
   % network performs.
   genFunction(net,'myNeuralNetworkFunction');
   y = myNeuralNetworkFunction(x,xi,ai);
end
if (false)
   % Generate a matrix-only MATLAB function for neural
network code
   % generation with MATLAB Coder tools.
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','y
es');
   x1 = cell2mat(x(1,:));
```

```
  x2 = cell2mat(x(2,:));
  xi1 = cell2mat(xi(1,:));
  xi2 = cell2mat(xi(2,:));
  y = myNeuralNetworkFunction(x1,x2,xi1,xi2);
end
if (false)
  % Generate a Simulink diagram for simulation or
deployment with.
  % Simulink Coder tools.
  gensim(net);
end
Functions
function [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~)
%MYNEURALNETWORKFUNCTION neural network
simulation function.
% Auto-generated by MATLAB, 24-Feb-2022 22:06:43.
% [Y,Xf,Af] = myNeuralNetworkFunction(X,Xi,~) takes these
arguments:
%   X = 2xTS cell, 2 inputs over TS timesteps
%   Each X{1,ts} = 7xQ matrix, input #1 at timestep ts.
%   Each X{2,ts} = 1xQ matrix, input #2 at timestep ts.
%   Xi = 2x2 cell 2, initial 2 input delay states.
%   Each Xi{1,ts} = 7xQ matrix, initial states for input #1.
%   Each Xi{2,ts} = 1xQ matrix, initial states for input #2.
%   Ai = 2x0 cell 2, initial 2 layer delay states.
%   Each Ai{1,ts} = 20xQ matrix, initial states for layer #1.
%   Each Ai{2,ts} = 1xQ matrix, initial states for layer #2.
% and returns:
%   Y = 1xTS cell of 2 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%   Xf = 2x2 cell 2, final 2 input delay states.
%   Each Xf{1,ts} = 7xQ matrix, final states for input #1.
%   Each Xf{2,ts} = 1xQ matrix, final states for input #2.
%   Af = 2x0 cell 2, final 0 layer delay states.
%   Each Af{1ts} = 20xQ matrix, final states for layer #1.
%   Each Af{2ts} = 1xQ matrix, final states for layer #2.
% where Q is number of samples (or series) and TS is the
number of timesteps.
%#ok<*RPMT0>
% ===== NEURAL NETWORK CONSTANTS =====
% Input 1
x1_step1.xoffset = [-1.15679600086175;-4.369699629409;-
2.33624851673967;-1.76309099372366;-
0.778566489321537;-2.26055715018236;-
1.59913514032293];
x1_step1.gain =
[0.491133863460997;0.346716282490431;0.419719790920
162;0.365711939877535;0.555341278279453;0.518808046
703778;0.464754815054487];
x1_step1.ymin = -1;
% Input 2
x2_step1.xoffset = -2.38387416200587;
x2_step1.gain = 0.390034461783813;
x2_step1.ymin = -1;
% Layer 1
b1 = [1.5783466954572125118;...
% Layer 2
b2 = -0.74030895639654115126;...
% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.390034461783813;
y1_step1.xoffset = -2.38387416200587;
% ===== SIMULATION ========
% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
  X = {X};
end
if (nargin < 2), error('Initial input states Xi argument
needed.'); end
% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
  Q = size(X{1},2); % samples/series
elseif ~isempty(Xi)
  Q = size(Xi{1},2);
else
  Q = 0;
end
% Input 1 Delay States
Xd1 = cell(1,3);
for ts=1:2
  Xd1{ts} = mapminmax_apply(Xi{1,ts},x1_step1);
end
% Input 2 Delay States
Xd2 = cell(1,3);
for ts=1:2
  Xd2{ts} = mapminmax_apply(Xi{2,ts},x2_step1);
end
% Allocate Outputs
Y = cell(1,TS);
% Time loop
for ts=1:TS

  % Rotating delay state position
  xdts = mod(ts+1,3)+1;
  % Input 1
  Xd1{xdts} = mapminmax_apply(X{1,ts},x1_step1);
  % Input 2
  Xd2{xdts} = mapminmax_apply(X{2,ts},x2_step1);
  % Layer 1
  tapdelay1 = cat(1,Xd1{mod(xdts-[1 2]-1,3)+1});
  tapdelay2 = cat(1,Xd2{mod(xdts-[1 2]-1,3)+1});
  a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*tapdelay1 +
IW1_2*tapdelay2);
  % Layer 2
  a2 = repmat(b2,1,Q) + LW2_1*a1;
  % Output 1
  Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end
% Final Delay States
finalxts = TS+(1:2);
xits = finalxts(finalxts<=2);
xts = finalxts(finalxts>2)-2;
Xf = [Xi(:,xits) X(:,xts)];
Af = cell(2,0);
% Format Output Arguments
if ~isCellX
  Y = cell2mat(Y);
end
end
% ===== MODULE FUNCTIONS ========
% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
```

```
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end
% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end
% Map Minimum and Maximum Output Reverse-Processing
Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```