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AN APPROACH OF COMBINING EMPIRICAL
MODE DECOMPOSITION AND NEURAL
NETWORK LEARNING FOR CURRENCY
CRISIS FORECASTING

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Abstract

This paper presents a hybrid model for predicting the occurrence of currency crises by using the artificial intelligence tools. The model combines the learning ability of the artificial neural network (ANN) with the inference mechanism of the empirical mode decomposition (EMD) technique. Thus, for a better detection of currency crises emergence, an EMD-ANN model based on the event analysis approach is proposed. In this method, the time series to be analyzed is first decomposed into several intrinsic mode components with different time scales. The different intrinsic mode components are then exploited by a neural network model in order to predict a future crisis. For illustration purposes, the proposed EMD-ANN learning approach is applied to exchange rate data of Turkish Lira to evaluate the probability of a currency crisis. We find evidence that the proposed EMD-ANN model leads to a good prediction of this type of crisis. Significantly, the model can thus lead to a somewhat more prescriptive modeling approach based on the determination of causal mechanisms towards finding ways to prevent currency crises.

ملخص

تعرض هذه الورقة نموذج للتنبؤ بحدوث أزمات العملة باستخدام أدوات الذكاء الاصطناعي . يجمع هذا النموذج بين القدرة على التعلم من الشبكة العصبية الاصطناعية (ANN) مع آلية الاستدلال على تقنية التحلل التجريبية (EMD) وذلك ، فمن أجل تحسين الكشف عن ظهور أزمات العملة ، نقترح نموذج EMD – ANN على أساس نهج تحليل الحدث .في هذه الطريقة ، يتم تحليل السلسلة الزمنية إلى عدة عناصر جوهرية مع وضع جداول زمنية مختلفة .ثم يتم استكشافها على مختلف المكونات الجوهرية وذلك لوضع نموذج الشبكة العصبية للتنبؤ بحدوث الأزمة في المستقبل .ولأغراض التوضيح، يتم تطبيق النهج المقترح EMD – ANN لتبادل بيانات سعر الليرة التركية لتقييم احتمال حدوث أزمة في العملة .نجد أدلة على أن المقترح EMD – ANN هو فعلا نموذج يؤدي إلى التنبؤ الجيد لهذا النوع من الأزمات .إلى حد كبير ، يمكن للنموذج يؤدي بالتالي الى نهج النمذجة إلى حد ما أكثر إلزامية استنادا إلى تحديد الآليات السببية من أجل إيجاد سبل لمنع حدوث أزمات العملة.

1. Introduction

Many crises of financial origin took place during the 1990's and currency systems have often played the major role within the observed dynamics. Thus, the sudden currencies' depreciation experienced by the European Monetary System (EMS), Latin America or Asia has prompted many studies seeking to model situations of vulnerability and exchange rate depreciation. The different generations of currency crises models have therefore enabled the development of several tests regarding the optimal monetary policy to implement in such situations.

Many emerging economies have benefited from substantial inflows in direct and portfolio investment. However, especially when short-term flows are concerned, changes in investors' attitude -often motivated by concerns related to the accumulation of public debt or financial imbalances - have often determined sudden capital outflows. Since 1994, these reversals have generated important financial turmoil in most Latin American countries, a part of Southeast Asia, and some countries in transition. These crises have often been aggravated by financial contagion, during which liquidity suddenly dried up in some countries, not because of changing of fundamentals of their economy, but because of common characteristics with other economies that lost market confidence. Experiences show that the risk of contagion increases when news on the financial health of a country is limited.

The increasing integration of economies is reflected by a rise in the systemic risk and by a multiplication of crises over the recent years in some developing countries. These successive crises were often followed by bailouts insured by international institutions (especially IMF) in order to restore confidence and limit the slowdown in global economic growth. These successive crises are usually triggered by a brutal depreciation of exchange rate of domestic currency.

In this context, the literature on currency crises has experienced a rapid growth. Its aim is to build a successful model for crisis forecasting, which can detect the emergence of problems in the foreign exchange markets in order to help countries to avoid crises.

Due to the high fluctuations of financial time series, it is difficult to use a single technique to capture its non-linearities and accurately describe its moving trend. Hence, a novel hybrid intelligent forecasting model, based on empirical mode decomposition (EMD) and neural network (ANN), is proposed in this paper. EMD can adaptively decompose the dataset into a number of independent intrinsic mode components (IMC) and a residue. These IMC could represent factors that affect exchange rate movements. These IMC which have different scales will represent the input layer for the proposed neural network learning system. The probability of crisis will then be the output layer of the neural network. Successful forecasting application on the Turkish exchange rate will demonstrate the feasibility and validity of the presented model.

In the proposed EMD-ANN approach, the exchange rate - a typical financial indicator reflecting changes in economic conditions - is chosen. Then, the EMD algorithm is applied on the exchange rate data and the IMC of the exchange rate series with different scales are obtained. Consequently, the relation between these different IMC and the probability of crisis is explored by a back-propagation neural network algorithm.

The distinct feature of the proposed model is that it uses only one indicator (the exchange rate). However, most previous studies (i.e. several statistical-based models, structural analysis models and some artificial intelligence methodologies), use different financial indicators related to crisis situations. However, these indicators are usually hard to obtain, mainly because disastrous financial crises occur rarely, or over a very short period of time. Another

important characteristic of this study is that the exchange rate data is used to judge whether the economic condition is approaching a crisis state or not.

The paper is articulated as follows: section 2 gives a literature review on currency crises. Some empirical evidence is developed in section 3. Section 4 describes some previous forecasting models of currency crises. The construction of the EMD-ANN system and its benchmarks is discussed in section 5. The empirical results are presented and interpreted in section 6. Finally, in section 7, we provide some conclusions and considerations for further researches.

2. Currency Crises Literature Review

Models of currency crises deal with situations in which a speculative attack is triggered in the foreign exchange market and causes important sudden depreciation of the exchange rate.

The first studies attempting to explain the occurrence of crises have been developed by Krugman in 1979. According to Krugman (1979), economic programs implemented by public authorities that are incompatible with a fixed exchange rate regime are the main cause of the outbreak of a crisis.

The first models have shown that the origin of currency crises comes from the weakness of fundamental economic variables typically related to expansionary monetary and fiscal policies. Krugman's model shows that under a fixed exchange rate, an expansion of domestic credit higher than the money demand leads to a gradual, but inexorable, decline in international reserves and ultimately to a speculative attack on the currency. This attack brutally depletes reserves and forces the authorities to abandon the parity. The attack is justified by the fact that agents understand that the fixed exchange rate regime will collapse, followed by capital losses on their holdings in domestic currency. In terms of indicators, this model suggests that the months preceding a currency crisis are characterized by a progressive decline in reserves, and a rapid rise in domestic credit compared with money demand.

A number of extensions have been added to this basic model. They showed that a speculative attack is usually preceded by an appreciation of the real exchange rate and a deterioration of trade balances. These results derive from models where fiscal policy and expansionary credit lead to greater demand in both tradable goods (which causes deterioration in the trade balance) and non-tradable goods (which causes an increase in the relative price of these goods, and therefore an appreciation of the currency in real terms).

The different currency crises in the nineties have strained the predictive qualities of these models. Indeed, these models fail in taking into account financial globalization and the reversibility risk of capital flows. However, the speculative crisis that hit the EMS in the early nineties has contested the idea that the crisis would be preceded by deterioration in fundamentals, particularly a loss in foreign reserves.

Thus, a more recent stand of literature, the so-called second generation models, has been developed following the EMS crisis in 1992-1993 (Eichengreen and Wyplosz, 1993).

The second-generation models rely on the idea that abandoning fixed parity by the government is no longer exclusively linked to the inexorable loss in foreign reserves, but rather the result of an arbitrage between the advantages of the parity and the costs of abandonment. Typically, maintaining the parity may require economic policies (such as increasing interest rates) which may have adverse effects on other key variables (such as the unemployment rate).

Obstfeld (1994) explains the currency crisis as a result of the conflict between the fixed exchange rate regime and the government's willingness to pursue an expansionary monetary policy. When investors begin to form expectations concerning the abandonment of fixed

exchange rates, further pressures on interest rates are likely to push the government to abandon this exchange rate regime. This is more than a significant deterioration, ex ante, of macroeconomic fundamentals.

Therefore, this new generation of models is characterized by the existence of multiple equilibriums where government share represented as "optimizing" agents. In these circumstances, crises can be unpredictable and the probability of survival of an exchange rate regime depends upon the willingness of public authorities to pay conservationist costs. Hence, crises can occur even when initial macroeconomic conditions are sound.

The Asian crisis seems to differ from the description provided by these standard models for two main reasons (Krugman, 1998): first, the monetary and fiscal fundamentals were not significantly degraded; second, the authorities' ability to trespass a speculative attack was strong, due to the economic overheating observed in many countries from this zone.

The collapse of the Asian system has triggered a large debate on the existence of a third generation crisis (Radelet and Sachs, 1998; Corsetti, Pesenti and Roubini, 1998) having its roots in the banking and financial fragility of the economy. The crisis is thus reduced to a problem of banking panic.

The crisis may also result from a contagion effect related to the concept of "spillover effects", when the crisis in one market affects the economic and financial systems of the neighboring countries and make them vulnerable. Situations of "pure contagion" (Masson, 1998), which cannot be explained by fundamentals, are also possible.

3. Empirical Evidence

Sachs, Tornell and Velasco (1996) tested the hypothesis on countries affected by the Mexican crisis. They found that the ratio of short-term debt to total capital flows was higher than in the other countries not affected by crisis. The authors used a simple model based on three factors that determine whether a country is more vulnerable or not to a financial crisis: a high appreciation of real exchange rate, a recent explosion in loans and a low level of foreign reserves.

In an attempt to diagnose the crisis in Southeast Asia, Radelet and Sachs (1998) found that the ratio of short-term debt to foreign exchange reserves helps in predicting large reversals of capital flows. Rodrik and Velasco (1999) obtain results in the same line, revealing that greater short-term exposure is associated with more severe crises in the case of capital outflow.

Frankel and Rose (1996) examined the composition and level of debt and a variety of macroeconomic factors. They found that currency crises occur when output growth is low, the growth of domestic credit is high, the level of foreign interest rates is high and the ratio of FDI/debt is low.

In a study on countries with low and medium income, Milesi-Ferretti and Razin (1998) found that domestic factors (such as low foreign exchange reserves) as well as external factors (such as deteriorated terms of exchange) can trigger currency crises. The authors found no effect of liquidity on these crises. However, when the sample is broadened to include the recent crisis, the liquidity variables become significant (Berg and Patillo, 1999; Bussiere and Mulder, 1999). In addition to this result, in a study identifying variables responsible of the crises in 1994 (Mexico), 1997 (Asia) and 1998 (Russia), Bussiere and Mulder (1999) concluded that these variables are consistent with those used by IMF in implementing "early warning signals" and that the presence of an IMF program significantly reduces the importance of the crisis.

Detragiache and Spilimbergo (2001) showed that for a given level of external debt, the probability of a crisis increases with the proportion of short-term debt and decreases with foreign exchange reserves.

Eichengreen, Rose and Wyplosz (1994) presented an empirical analysis of speculative attacks on the fixed exchange rate and concluded that there is an impossibility of rejecting the null hypothesis of the presence of significant differences in the behavior of macroeconomic variables in periods of crisis and during "quiet" periods in the countries composing the European Monetary System.

Kaminsky and Reinhart (1999) analyzed the potential links between banking crises and currency crises. They found that problems disrupting the banking sector typically precede a currency crisis; the latter even worsens the banking crisis by creating a vicious circle. Furthermore, it is clear that financial liberalization often precedes banking crises.

Kaminsky, Reinhart and Lizondo (1998) tried to empirically explain currency crises in order to provide an early warning system that is able to detect the evolution of indicators that tend to show unusual behavior during the periods preceding a crisis. Indeed, when the value of an indicator exceeds a certain "threshold", one can interpret it as an alarming signal indicating that a currency crisis will occur in the next 24 months. The indicators, which have been chosen by the authors, are the amount of exports, the deviation of the exchange rate from its average, the ratio M2/foreign exchange reserves, and the output and the stock prices.

It is clear from this empirical work that crises are assumed to be the same, since researchers used the same battery of indicators for all crisis episodes independently of the category to which they belong (1st, 2nd or 3rd generation)

Hence, Kaminsky (2006) used a new method in order to classify 96 currency crises in 20 countries between 1970 and 2001. This empirical classification clearly reflected the variety of crises presented in the theoretical literature proving that the attacks were not the same.

4. Currency Crises Forecasting Models

As a result of the recent crises in emerging markets and the evolution of financial markets, financial research is increasingly focusing on the study of forces that contribute to the emergence of a financial crisis.

Recent literature has been directed towards the identification of indicators that could explain the burst of a currency crisis. The objective is to determine if the causes of currency crises can be anticipated in advance, in order to allow governments to adopt preventive measures.

The empirical analyses use two different methods to identify leading indicators of the crisis.

The first one is the warning signals approach which consists in following the evolution of a number of economic indicators that tend to behave systematically differently before the crisis compared to "normal" periods. Notable examples include Alvarez- Plata and Schrooten (2004), Kaminsky et al.(1998), Kaminsky (1999), Kaminsky and Reinhart (1999), Goldstein et al.(2000), and Peng and Bajona (2008). In their models, individual variables such as the real effective exchange rate, the stock prices or the reserves level are considered as "signals" indicating that a country is potentially in a state of crisis whenever they exceed a specified threshold. While intuitively appealing, signal models are essentially univariate by nature. Kaminsky (1999) suggested a way of combining individual signals to form a composite index for prediction purposes, but this method does not solve all problems. For example, assuming that some of signal variables are closely correlated, means that each of them may have a very high noise-to-signals ratio, even though one of them does not significantly contribute to the analysis. The problem here is that the noise-to-signal weights are themselves based on a univariate analysis.

The second approach identifies variables that help to statistically anticipate the crisis and directly estimates the probability of occurrence of a crisis on the basis of an explicit model, knowing that the indicators are measured simultaneously. We can cite the work of Frankel and Rose (1996), Klein and Marion (1997), Goldfajn and Valdés (1998). These authors use logit or probit models to assess the probability of a crisis at time $t + i$, based on a set of explanatory variables observed int. This type of financial crisis models focus on panel data analysis employing discrete choice techniques in which macroeconomic and financial data are used to explain discrete crisis events that could occur in different countries. Eichengreen et al.(1996) adopted a probit model to analyze and predict crises in industrial countries using quarterly data on the period between 1959 and 1993. Likewise, Berg and Pattillo (1999) also used a probit model to predict currency crisis. Kumar et al. (2003), Beckmann et al.(2006), Kalotychou and Staikouras (2006) and Bussiere and Fratzscher (2006)used logit and multinomial logit models to predict currency crashes in emerging markets and financial crises and obtained good performance. In addition, Cipollini and Kapetanios (2008) and Mouratidis (2008) applied the dynamic analysis model and the Bayesian Markov switching approach to identify signals of financial crises. However, these models are parametric statistical models, and include several statistical assumptions leading to weak robustness. Since a currency crisis is a rare event with nonlinear characteristics, it is difficult for these statistical models to capture all the possible crises at all times. Furthermore, a large number of data on different variables needs to be collected to construct these models.

Hence, financial studies generally seek to identify a set of macroeconomic, financial and real indicators likely to be responsible for triggering the currency crisis that could serve as leading indicators or predictive factors of the vulnerability of a country to a currency crisis. These indicators should enable governments to determine the context in which the country would be more vulnerable to attacks in order to anticipate the crisis and intervene to prevent its outbreak. The results of the empirical tests are different, sometimes in conflict and highlight many fundamental variables.

Therefore, a new approach to predict financial crises has been developed over the recent years; it is based on some emerging computational techniques such as artificial intelligence methods, based upon technical or volatility indicators. For example, Niemira and Satty (2004) proposed an analytic network process (ANP) model for financial crisis forecasting. Kim and Moon (2001) adopted a computable general equilibrium (CGE) model to analyze the relationship between the currency crisis and the Korean industrial structure. Kim et al.(2004) applied a back-propagation neural network (BPNN)model to predict economic crisis in South Korea using the Korean stock market index. Yu et al.(2006) employed a general regression neural network (GRNN) to predict the currency crisis in Southeast Asian economies using some currency volatility indicators. Celik and Karapete (2007) used a feed-forward neural network (FFNN) model for forecasting banking crisis and obtained successful solutions. In addition, Son et al.(2008) and Lin et al.(2008) adopted some machine learning approaches such as fuzzy experts system to construct early-warning systems for financial crisis prediction.

However, it is worth noting that these methods depend on the selection of the different indicators. Usually, the randomness in the selection of indicators of ten leads to some unexpected results. In other words, different selections will lead to different prediction results.

The main objective of this paper is to develop a preventive model that would be able to signal in advance any problem or tension on the foreign exchange market. We propose an empirical mode decomposition system which is a new learning paradigm combined with neural

networks for currency crisis forecasting. The neural network algorithm used in this study is the back-propagation one, a popular tool for pattern recognition.

5. Methodology Formulation

5.1. An overview of artificial neural networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by biological nervous systems, such as the brain process information. The key element of this paradigm is the structure of the information processing system. It is composed by a large number of highly interconnected processing elements (neurons) working together to solve specific problems. Figure 1 illustrates a neural network structure as defined by various previous works:

The ANNs learn through examples. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

One of the most commonly used supervised ANN models is the back-propagation neural network (BBNN). Back-propagation algorithm is one of the well-known algorithms in neural networks. This algorithm is essentially a network of simple processing elements working together to produce a complex output. These elements or nodes are arranged into different layers: input, hidden and output layers.

The learning process of a neural network tries to find the best outputs by minimizing the error function. The algorithm can first be trained by using an in-sample dataset and then be applied on an out-of-sample dataset for prediction. This ability to learn through examples and the ability to be generalized to new situations is the most attractive feature of the neural network paradigm. Basically, the BPNN-based forecasting model can be summarized as follows:

The network receives the information in the input layer as a set of explanatory variables which are then processed using one or more hidden layers containing one or more neurons. In this phase, variables are weighted by connection weights α and transformed by the activation function Q . We obtain a new set of variables h_1, h_2, \dots, h_n , so that:

$$h_j = Q(\alpha_{0j} + \sum_{i=1}^n \alpha_{ij} X_i) \quad (1)$$

In turn, variables h_j are weighted by the connection weights β and processed by the transfer function F (see figure 1). Each output is interpreted by the following formula:

$$Y_k = F[\beta_{0k} + \sum_{j=1}^m \beta_{jk}(h_j)] \quad (2)$$

Where:

- X_1, X_2, \dots, X_n : are the explanatory (exogenous) variables in the input layer;
- $w(\alpha, \beta)$: is a set of model parameters (connection weights);
- h_1, h_2, \dots, h_m : is the number of neurons in the hidden layer;
- $Q(X)$: is the activation function of neurons;
- $F(X)$: is the transfer function
- Y_1, Y_2, \dots, Y_p : are the explained (endogenous) variables.

The main reason for selecting BPNN as a predictor is that a BPNN is often viewed as a “universal approximate”. Hornik *et al.*(1989) found that a three-layer BPNN with an identified transfer function in the output unit and a logistic functions in the middle-layer units can well approximate arbitrarily any continuous function, given a sufficient amount of middle-layer units. Neural networks have the ability to provide flexible mapping between inputs and outputs. In this study, we utilize the three-layer BPNN method for modeling and forecasting.

The general principle of the back-propagation algorithm is giving to the network a large number of examples for which the inputs and their associated outputs are known and weights are adjusted to correct the error of the network (i.e. the difference between targets and obtained responses). Thus, learning is seen as an optimization problem to find the network coefficients which minimize a cost function. The most used cost function is the mean square error (MSE) where error represents the difference between the network outputs and the real values.

One of the major BPNN advantages is that their learning algorithms are applicable to all types of networks. One is free in choosing the best architecture adapted to the problem, and whatever the network structure, one can always use the same set of learning algorithms. This flexibility allows implementation including networks whose architecture depends strongly on the structure of problems which are expressed by equations.

The most frequent problem that appears during the learning process of the ANN is over fitting. If the ANN learns insufficiently or inappropriately, it will give incorrect results when it receives some slightly different data. To avoid over fitting, the performance of the trained network should then be compared to another set called a validation set. This strategy should provide a better generalization of the model. It consists in monitoring the evolution of the cost function on a validation dataset and stopping the iterations as soon as the calculated cost on this dataset starts increasing. Once the network is executed, one should always apply tests to verify if it responds correctly. In the test phase, a part of the sample is simply removed and conserved for out-of-sample tests. For example, we can use 60% of the sample for learning, 20% for validation and 20% for testing.

5.2. An overview of the empirical mode decomposition system

Huang *et al.* (1998, 1999) developed the Hilbert-Huang transformation¹ (HHT) to decompose a time-dependent data series into its individual characteristic oscillations with the so-called empirical mode decomposition (EMD). This adaptive technique is derived from the simple assumption that any signal consists of different intrinsic mode components (IMC), each of them representing an embedded characteristic oscillation on a separate time-scale. An IMC is defined by two criteria: *i*) the number of extreme a and the number of zero crossings must either equal or differ at most by one, and, *ii*) at any instant in time, the mean value of the envelope defined by the local maxima and the envelope of the local minima is equal to zero. The first criterion is almost similar to the narrow band requirement of a Gaussian process, while the latter condition transforms a global requirement into a local one, to ensure the instantaneous frequency if necessary. In other words, the EMD is based on the direct extraction of the energy associated with various intrinsic time scales.

A sifting process is designed to extract IMCs level by level. First, the IMC with the highest frequency riding on the lower frequency part of the data is extracted, and then the IMC with the next highest frequency is extracted from the differences between the data and the extracted IMC. The iterations continue until no IMC is contained in the residual.

The starting point of the empirical mode decomposition is to consider oscillations in signals at a very local level. In fact, if we look at the evolution of a signal $x(t)$ between two consecutive extrema (two minima occurring at times t^- and t^+), we can heuristically define a (local) high-frequency part $d(t)$, $t^- \leq t \leq t^+$ or local detail, which corresponds to the oscillation that ends at the two minima and that passes through the maximum which necessarily exists between them. For the picture to be complete, one still has to identify the

¹Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis.", Proc. R. Soc. Lond. A (1998) 454, 903–995.
http://keck.ucsf.edu/~schenk/Huang_etal98.pdf

corresponding (local) low-frequency part $m(t)$, or local trend, so that $x(t) = m(t) + d(t)$ for $t^- \leq t \leq t^+$. Assuming that this is done in some proper way for all the oscillations composing the global signal, the procedure can then be applied to the residual consisting of all local trends, and the constitutive components of a signal can therefore be iteratively extracted.

Given a signal $x(t)$, the effective algorithm of EMD can be summarized as follows:

1. Identify all extrema of $x(t)$;
2. Interpolate between minima (respectively, maxima), ending up with some envelope $e_{min}(t)$ (respectively, $e_{max}(t)$);
3. Compute the mean $m(t) = (e_{min}(t) + e_{max}(t))/2$;
4. Extract the detail $d(t) = x(t) - m(t)$;
5. Check the properties of $d(t)$:
6. If it is an IMC, denote $d(t)$ as the i^{th} IMC and replace $x(t)$ with the residual $r(t) = x(t) - d(t)$. The i^{th} IMC is often denoted as $c_i(t)$ and i is its index;
7. If not, replace $x(t)$ with $d(t)$;
8. Repeat steps 1 to 5 until the residual satisfies some stopping criterion.

One stopping criterion proposed by Huang *et al.* (2003) for extracting an IMC is iterating a predefined number of times after the residual satisfies the restriction that the number of zero-crossings and extrema do not differ by more than one and the whole sifting process can be stopped by any of the following predetermined criteria: either when the component $c_i(t)$ or the residual $r(t)$ becomes so small that it is less than the predetermined value of a substantial consequence, or when the residual $r(t)$ becomes a monotonic function from which no more IMC can be extracted. The original time series can thus be expressed as the sum of IMCs and the residual:

$$x(t) = \sum_{i=1}^N c_i(t) + r(t) \quad (3)$$

Where N is the number of IMCs, and $r(t)$ means the final residual.

The advantages of an EMD can be briefly summarized as follows: first, it can reduce any type of data, from non-stationary and nonlinear processes into simple independent intrinsic mode functions; second, since the decomposition is based on the local characteristic time scale of the data and only extrema are used in the sifting process, it is local, self-adaptive, concretely implicational and highly efficient.

6. Empirical Study

6.1. Data

In order to illustrate and verify the proposed EMD-ANN model, we conduct an analysis on the Republic of Turkey, a country in MENA region.

The dataset is the daily exchange rate of the Turkish Lira against the US Dollar obtained from the Pacific Exchange Rate Service.² The main reason for choosing this currency is its representativeness of the MENA region which suffered from the 1994 currency crisis and 2000-2001 financial and currency crisis. The sample data covers the period from January 1991 to December 2009, with a total of 4958 observations (19 years). For purposes of training and testing, the dataset is divided into two parts, in-sample and out-of-sample. The in-sample (60% of data) part goes from 01/01/1991 to 05/27/2002 (2975 observations). It is used for the neural network model building. The out-of-sample part (40% of data) goes from

²<http://fx.sauder.ubc.ca/>

05/28/2002 to 12/31/2009 (1983 observations), and is used for validation and test. Figure 2 shows the data series of USD/TRY.

The Turkish economy has been hit by two crises in the two last decades. The first one occurred at the beginning of 1994. At that time, the exchange rate was under a managed float regime. In the aftermath of the crisis, the Turkish economy contracted by 6%, the highest level of annual output loss in its history. In the first quarter of 1994, the Turkish Lira was devalued by more than 50% against the US Dollar, the Central Bank lost half of its reserves, interest rates skyrocketed, and the inflation rate reached three digit levels.

The second crisis erupted in the second half of November 2000, in the midst of an exchange rate based stabilization program. In response to the turmoil, a new letter of intent was presented by the government to the International Monetary Fund (IMF) and calmed market pressure. However, by the end of December, the interest rates were almost four times higher than the levels at the beginning of November and five times higher than the pre-announced (at the outset of 2000-2002 program) level. This unsustainable situation ended on February 19, 2001 when the Prime Minister announced that the country experienced a severe political crisis, which had ignited an equally serious economic crisis on the highly sensitive markets. As a consequence, overnight rates jumped to unprecedented levels of 6,200 percent. Three days later, the exchange rate system collapsed, and Turkey declared that it was going to implement a floating exchange rate system.

6.2. Crisis Model

According to Eichengreen *et al.* (1995, 1996), currency crisis can be measured using the EMP (Exchange Market Pressure) index, which is calculated as follows:

$$EMP_{i,t} = \alpha \Delta e_{i,t} + \beta \Delta(i_{i,t} - i_{USD,t}) - \gamma \Delta r_{i,t} \quad (4)$$

Where:

- $\Delta e_{i,t}$ is the deflation rate of the nominal exchange rate of currency i at time t ;
- $\Delta(i_{i,t} - i_{USD,t})$ is the change of the interest rate differential between currency i and US Dollar;
- $\Delta r_{i,t}$ is the change rate of the foreign exchange reserves;
- α, β, γ are the weights insuring that the variances are equal among these three parts.

Kaminsky *et al.* (1998), Kaminsky (1998), Kaminsky and Reinhart (1999) and Goldstein *et al.* (2000) built on Eichengreen *et al.* (1995, 1996), but they excluded interest rate differential from their index. Hence, Kaminsky and Reinhart (1999) formula becomes:

$$EMP = (\Delta e/e) - (\sigma_e/\sigma_R)(\Delta R/R) \quad (5)$$

Where:

- $\Delta e/e$ is the rate of change of the exchange rate;
- $\Delta R/R$ is the rate of change of the foreign exchange reserves;
- σ_e is the standard deviation of $\Delta e/e$, and σ_R is the standard deviation of $\Delta R/R$.

The reason for removing the interest rate change part is that some countries adopt interest rate control which forces this variable to have no significant explanatory role for the currency crisis. The function of σ_e/σ_R is similar to the function of α, β, γ , i.e. insure variances equality.

However, a major drawback of this approach is that the threshold value used to identify the speculative attack is somewhat arbitrary. Kaminsky *et al.* (1998), for example, define crises as periods during which the exchange market pressure index is at least three standard deviations above the mean, while in Edison (2000), a crisis is detected as soon as the index is

above its mean by more than 2.5 standard deviations. We adopt the Kaminsky and Reinhart (1999) classification. The currency crises are defined as the situation when the observed EMP is greater than its mean by more than 3 standard deviations; otherwise no currency crisis is going to happen, e.g. :

$$crisis_{i,t} = \begin{cases} 1 & \text{if } EMP_{i,t} > \mu_{EMP_i} + 3\sigma_{EMP_i} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Where μ_{EMP_i} and σ_{EMP_i} are calculated based on the in-sample data and used to define the crisis for both in-sample and out-of-sample data.

6.3. EMD-ANN analysis

In the EMD analysis, the first step is to identify the specific event of interest and define the indicator (i.e. time series) to be analyzed. In our study, a currency in the MENA region is analyzed by fully EMD-ANN procedure. The dataset of Turkish Lira is decomposed into some IMCs via the Hilbert-Huang transformation technique.

Figure 3 presents the results of decomposition. It is easy to notice that the USD/TRY data consists of 10 IMCs and one residue. These IMCs represent the basis of the proposed EMD-ANN learning system.

We include the IMCs and residue in the neural model as input variables for the final multi-scale learning. The output variable represents the probability for a currency crisis to occur (equation 6). If the probability is greater than a threshold value, it is interpreted as a warning signal that a currency crisis will happen. Otherwise, there is no expected currency crisis.

The IMCs derived by applying EMD to the dataset are shown in figure 3. The sifting processes produce 11 IMCs for daily data. All the IMCs are listed following the exact order in which they are extracted, that is, from the highest frequency to the lowest frequency, the last one being the residue.

All the IMCs present changing frequencies and amplitudes, which are different depending on each IMC. With the frequency changing from high to low, the amplitudes of the IMCs are becoming larger: for example, all the amplitudes of IMC1 are smaller than 0.1, but the amplitudes of IMC10 attain 2. The residue is a slowly varying mode around the long-term average.

From this decomposition, a neural network model analyzes the components for final multi-scale learning. The network has eleven neurons in the input layer (corresponding to the 11 IMCs), and one neuron in the output layer (corresponding to the presence or absence of crisis). The number of neurons in the hidden layer is fixed at 10. Note that the number of hidden nodes is determined by trial-and-error. This simple structure is able to guarantee a good generalization on new data.

The next step is to use the IMCs (input data) to train the neural network model. In this step, the first task is to determine the training targets using equation 6. Based on the IMCs and the training targets, the neural network training process is easy to implement. The final step is to test the trained neural network for verification purposes.

The simulation is conducted under MATLAB r2008b. The configuration of our ANN is characterized by the following steps:³

- Dividing the dataset into two sets, the training series (60% of data), and validation and test set (40% of data).
- Normalization of data (all data values are included in the interval [-1, 1]).

³ We determined the neural network parameters after a large number of tests since there is no general rule that can easily define these parameters.

- Creation of an ANN with one hidden layer including 10 neurons. We chose a sigmoid hyperbolic tangent activation function (tansig).
- The learning function is Gradient Descent with momentum term (traingdm).
- The number of iterations is 10.000 epochs, the learning rate is 0.3, and the convergence rate is 0.6.

The neural network minimizes the mean square error (MSE). The learning stops when the MSE no longer decreases after 10.000 iterations.

The neural network provides a continuous output with values between zero and one. We have already defined a threshold and when the output reaches this threshold, a warning signal about a possible currency crisis is released.

6.4. Results

The performance assessment of a warning tool is traditionally based on two measures which can be defined from the matrix shown in Table 1.

Let A represents the number of true signals released when a crisis is indeed taking place and B is the number of false or noise signals when no crisis is on stake. C is the number of false silences (no-signal) and D is the number of true silences. The table indicates if a signal (or a no-signal) occurs during one year (12 months).

We begin by assessing the quality of our system; we thus calculate conditional probabilities based upon the cell counts in the contingency table. We calculate the percentage of time over which the indicator released a signal when there was a crisis. In this case we are looking only at the “crisis” column of the contingency table to compute the probability that a signal was released. This probability is given by $A/(A + C)$. A high probability is associated with a good quality of the model. We also need to know how noisy the signal is. In particular, if no crisis occurs over the forecast horizon, we have to determine how often the indicator released a signal. Looking at the “no crisis” column of the contingency table, we compute the ratio $B/(B + D)$. A lower probability is a signal of a good model.

Let the noise-to-signal ratio represent a measure of the background noise relative to the signal strength. The ratio is usually measured by the following equation:

$$NSR = \frac{B/(B+D)}{A/(A+C)} \quad (7)$$

The smaller the NSR is, the better the indicator is for signaling a currency crisis. Table 2 presents the performance results of our indicator (currency exchange rate):

The performance obtained using neural networks is good for our forecasting horizon since the NSR approaches zero. This very small NSR is associated with significant coverage, i.e.100%of crises. This implies that the proposed EMD-ANN learning approach is a very promising alternative for currency crisis forecasting.

This implies that all the currency crises (1994 and November 2000- February 2001)are successfully captured and supports our claim that crisis-related data are usually easily classified. However, the model also released one false signal while there was no crisis.

All in all, the proposed EMD-ANN tool performs well. The main reason is that the EMD produces some IMCs with different scales, which simplifies the problem. Furthermore, different IMCs with different scales include different news and, therefore, the neural network is able to extract more knowledge, thereby increasing the generalization ability of the neural network.

7. Conclusion

There is a wide agreement among financial economists and policy makers that in order to avoid the devastating damages of a currency crisis, we need to have an effective early warning system. We thus propose in this paper, to build up such system by using the EMD-ANN technique.

Two techniques, neural networks and empirical mode decomposition, have shown their ability to adapt to the complex field of currency crises. Neural networks are particularly characterised by an outstanding performance. Empirical mode decomposition techniques allowed us to decompose the currency crisis indicator in several independent components. The empirical results show that EMD-ANN model could provide accuracy rates that are as high as 100% for the dataset.

Moreover, if we suppose that a database of different currency crisis indicators is available, we will be able to build a database providing more detailed causal relationship among variables, hence suggesting potential policy decisions for increasing the chances to avoid crises. These relationships can also be the basis for theoretical modifications in the modelling approach to be implemented by further researches.

To sum up, this work provides the following main contribution: we proposed an estimate for the probabilities of occurrence of currency crisis, as well as an alternative to deal with the inherent nonlinearities of this problem. The main drawback of our work is the inability of this modelling to offer an economic explanation of the crisis and to detect potential economic indicators that are responsible for crisis. This limit comes from the fact that we have used only one explanatory financial indicator in our empirical study (the exchange rate).

Finally, a general approach to identify the relationships among the different variables can be the basis for further hypothesis testing on other important explanatory indicators of currency crises. Another significant area for future applications could be banking crises and stock market crashes.

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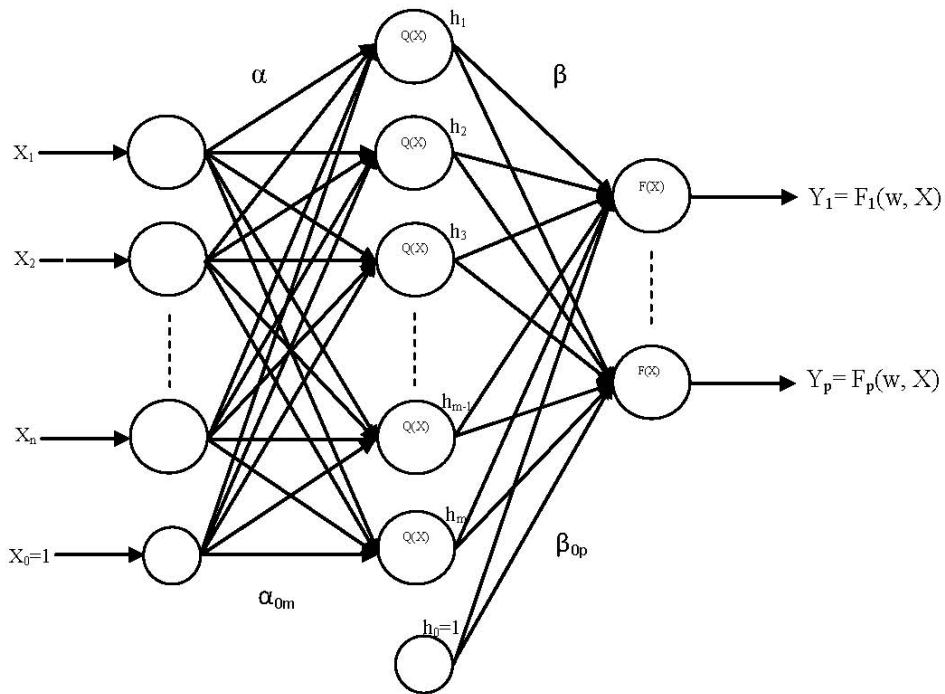
Table1: Contingency Table

	Crisis	No Crisis
Signal	A	B
No Signal	C	D

Table 2: Classification Results for the USD/TRY Exchange Rate

	Crisis	Non Crisis	Total
Signal	3	1	4
Non signal	0	15	15
Total	3	16	19
A/A+C	100%	---	
B/B+D	---	6%	
NSR	0.06		

Figure 1: General Architecture of a Neural Network



Source: Zhang, G., Hu, M.Y., (1998).

Figure 2: The Daily Spot USD/TRY from January 1991 to December 2009

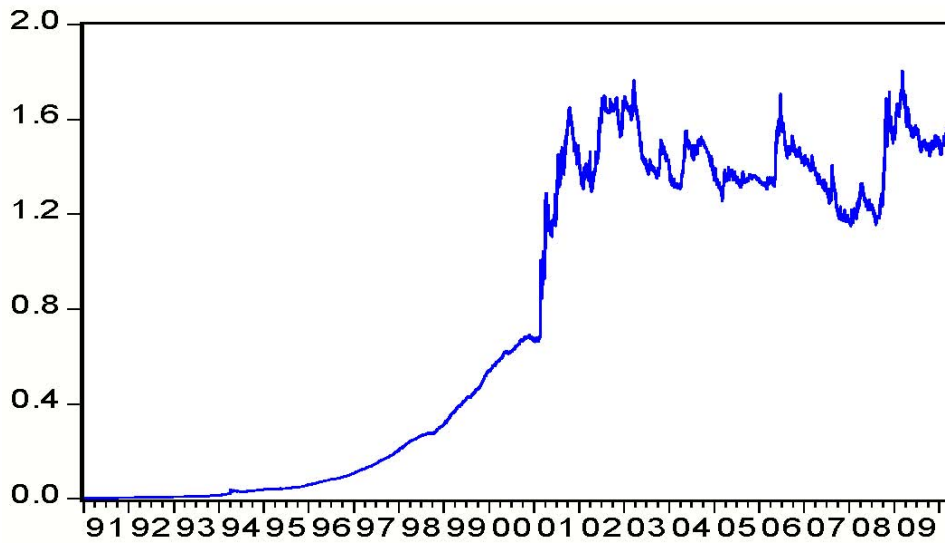


Figure 3: Empirical Mode Decomposition of USD/TRY Exchange Rate

