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 integrates the learning ability of the Artificial Neural network (ANN) with the inference mechanism of Empirical Mode Decomposition (EMD). Thus, for better detection of currency crises emergence, an EMD-ANN model based on event analysis approach is proposed. In this method, the time series to be analyzed are first decomposed into several intrinsic modes with different time scales. Consequently, the different intrinsic modes are then explored by a neural network model in order to predict future crisis financial events. For illustration purposes, the proposed EMD-ANN learning approach is applied to exchange rate data of Turkish Lira to evaluate the state of financial crisis. The empirical results show that the proposed EMD-ANN model leads to a good prediction of crisis. Significantly, the proposed 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.

JEL: G01, G17, C45, F31.

Key Words: Emerging Markets - Exchange Crisis - Artificial Neural Network - Early Warning System - Empirical Mode Decomposition.
I. Introduction

The Nineties were marked by many crises of financial origin, currency systems have often been the central of observed dynamics. Thus, the sudden depreciation of currencies recorded in 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 on choosing the optimal monetary policy in such situations.

Many emerging economies have benefited from substantial inflows of direct investment and portfolio investment. However, especially when short-term flows are concerned, changes in investors’ attitude- often motivated by preoccupations related to the accumulation of public debt or financial imbalances - have resulted in too many cases of sudden outflows capital. Since 1994, these reversals have contributed to serious financial crises in most Latin American countries, a part of Southeast Asia, and in some countries in transition. These crises have often been aggravated by border financial contagion, during which liquidity suddenly dried up in some countries, not because of changing of fundamentals of their economy, but because they had common characteristics with another economy that is losing market confidence. Experience shows that the risk of contagion increases when news on the financial health of a country are limited.

The increasing integration of economies is reflected by a rise in systemic risk (diffusion of economic crises in the world) and by a multiplication of crises in recent years in some developing countries. These successive crises have given rise to the establishment of a number of bailouts by international institutions (especially IMF) in order to restore confidence and limit the slowdown in global economic growth affected by these brutal shocks disturbing areas that have high rates of economic growth. These successive crises are usually triggered by a brutal depreciation of the exchange rate of local currency, which leads to a questioning of exchange market functioning of these countries.

In this context, especially in response to major crises that hit emerging markets, the literature on currency crises has rapidly become considerable, both on theory and on econometric predictions of crises.

The aim of this work is to try to build a successful model for forecasting, which can detect the emergence of problems on the foreign exchange markets in order to help countries to avoid a crisis.

Due to the fluctuation and complexity of the financial time series, it is difficult to use any single artificial technique to capture its non-stationary property and accurately describe its moving tendency. So a novel hybrid intelligent forecasting model based on empirical mode decomposition (EMD) and neural network is proposed. EMD can adaptively decompose the complicated raw data into a finite set of intrinsic mode functions (IMFs) or intrinsic mode composition (IMCs) and a residue, which have simpler frequency components and higher correlation. Tendencies of these IMFs and crisis index are forecasted by an ANN in which the kernel functions are appropriately chosen according to their different fluctuations. Successful forecasting application of crisis index concerning the Turkish exchange rate demonstrates the feasibility and validity of the presented model.
In the proposed EMD-ANN approach, exchange rate - a typical financial indicator reflecting changes in economic conditions - is chosen. Then the EMD algorithm is applied to the exchange rate data and the IMCs of the exchange rate series with different scales are obtained. Consequently, the internal correlation structures of different IMCs are explored by a back-propagation neural network model.

The distinct feature of the proposed model is that it uses one indicator (i.e. exchange rate) only. In most previous studies, however, several statistical-based models, structural analysis models, and some artificial intelligence methodologies, several financial indicators related to crisis situations, are used. These indicators, in real life situations, 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. The following section gives a literature review on currency crises. Then, it is followed by some empirical evidence in section. Section 4 describes some previous predicting models of currency crises. The construction of 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 give some conclusions and considerations for further research.

II. A review on currency crises

Models of currency crises deal with situations in which a speculative attack is triggered on the foreign exchange market and cause devaluation in a fixed exchange rate or a high sudden depreciation of the exchange rate in flexible exchange rate regime.

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

The first models have shown that the origin of currency crises comes from the weakness of fundamental economic variables typically related to monetary and fiscal policy too expansionary. The model of Krugman (1979) shows that under a fixed exchange rate, an expansion of domestic credit higher than 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, and in the absence of attack, they would suffer from capital loss on their holdings 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 the money demand.

A number of extensions have been made to this basic model in various ways. They showed that a speculative attack is usually preceded by an appreciation of real exchange rate and a deteriorating of trade balance. These results derive from models where fiscal policy and expansionary credit lead to greater demand in tradable goods (which causes deterioration in the trade balance) as well as non-tradable goods (which causes an increase in the relative price of these goods, and therefore an appreciation of the currency in real terms).
Moreover, models that introduce uncertainty about credit policy or level of loss reserves that the government is willing to accept in order to defend the parity show that domestic interest rates should increase when a crisis becomes likely.

The specifics of the currency crises of the nineties have strained the predictive qualities of these models. These models present indeed the fault of not integrating the context of 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 loss of foreign reserves.

Thus, a more recent work, the so-called second generation, have been developed following the EMS crisis of 1992-1993 (Eichengreen and Wyplosz, 1993), which constituted the first experience of financial globalization in developed countries.

The second-generation models rely on the idea that abandoning fixed parity by government is no longer exclusively tied to the inexorable loss of foreign reserves, but rather the result of a policy of arbitrage between the advantages of the parity and the costs in terms of objectives of an abandonment of this parity. Typically, the maintaining of the parity may require economic policies (such as rising interest rates) which may have adverse effects on other key variables (such as 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, pressures on interest rates which are resulted are likely to push the government to take effectively the decision to abandon this exchange rate regime. It 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 and the presentation of governments as "optimizer" agents. In these circumstances, crises can be unpredictable and the probability of survival of an exchange rate regime is the resolution of the authorities to pay for its conservation. So that, crises can justify themselves even when initial macroeconomic conditions are sounded.

The Asian crisis seems to get away from the standard models for two main reasons (Krugman, 1998): first, the monetary and fiscal fundamentals were not significantly degraded; second, the authorities’ ability to resist a speculative attack was strong due to economic overheating observed in many countries of that zone.

The collapse of the Asian system has trigged a large debate on the existence of a third generation crisis (Radelet and Sachs, 1998; Corsetti, Pesenti and Roubini, 1998) that centers the analysis on the problem of banking and financial fragility of economies. The crisis is thus reduced to a problem of banking panic at international flows of capital that transform an economy with good equilibrium to equilibrium of crisis.

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

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

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 help to predict large reversals of capital flows. Idem for Rodrik and Velasco (1999) whose empirical analysis revealed that greater short-term exposure is associated with more severe crises when there is capital outflow.

Frankel and Rose (1996) examined the composition and the debt level 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 (foreign direct investment) debt is low.

In a study covering low and middle income countries, Milesi-Ferretti and Razin (1998) found that domestic factors (such as low foreign exchange reserves) as well as external factors (such as worsening 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, Bussiere and Mulder concluded in a study identifying variables responsible of the crises of 1994 (Mexico), 1997 (Asia) and 1998 (Russia), that these variables are consistent with those used by IMF to the construction of "Early Warning Signals" and that the presence of an IMF program significantly reduces the depth of the crisis.

Detragiache and Spilimbergo (2001) found that for a given level of external debt, the probability of a crisis increases with the proportion of short-term debt and debt service arrears, 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 it was impossible to reject the null hypothesis that there were few significant differences in the behavior of macroeconomic variables in periods of crisis and during "quiet periods in the countries of 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 precede typically a currency crisis; the latter even worsen the banking crisis by creating a vicious circle. Furthermore, it is clear that financial liberalization often precedes banking crises.

In 1998, Kaminsky, Reinhart and Lizondo have tried to explain currency crises empirically in order to provide an early warning system able to observe the evolution of indicators that tend to show unusual behavior during the periods preceding a crisis. Indeed, when an indicator value exceeds a certain "threshold", this is interpreted as an alarming signal about a currency crisis which will occur in the next 24 months. The variables to be monitored by the authors are exports, deviation of the exchange rate of its average, ratio M2/foreign exchange reserves, production and 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 whatever the category to which they belong (1st, 2nd or 3rd generation, Sovereign debt\(^1\), Sudden Stops\(^2\)).

Also in 2006, Kaminsky has 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 proposed elsewhere in the literature for generations of theoretical models of currency crises proving that the attacks were not the same.

**IV. Prediction Modeling of Currency Crises**

As a result of the recent crises in emerging markets and the evolution of financial markets, the research focuses increasingly 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 release of a currency crisis. The objective was to determine if we can anticipate well in advance causes of currency crises, in order to allow governments to adopt preventive measures.

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

The first one is the warning signals approach which consist to follow the evolution of a number of economic indicators that tend to behave systematically differently before the crisis compared to "normal" periods. This type of financial crisis modeling is the signal approach. 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 real effective exchange rate or debt to GDP (Gross Domestic Product) levels are considered as "signals" indicating that a country is potentially in a state of crisis when they exceed a specified threshold. While intuitively appealing, signal models are essentially univariate in nature. Kaminsky (1999) suggested a way of combining individual signals to form a composite index for prediction purposes, but this combined method does not solve all problems. For example, assuming that some of the signal variables are very closely correlated; each of them may have a very high noise-to-signal ratio, even though all but one of them adds almost nothing to the collective analysis. The problem here is that the noise-to-signal weights are themselves based on univariate analysis.

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\(^1\) Sovereign or Government debt: Under the doctrine of sovereign immunity, the repayment of sovereign debt cannot be forced by the creditors and it is thus subject to compulsory rescheduling, interest rate reduction, or even repudiation. The only protection available to the creditors is threat of the loss of credibility and lowering of the international standing (the sovereign debt rating) of the country which may make it much more difficult to borrow in the future.

http://www.businessdictionary.com/definition/sovereign-debt.html

\(^2\) A sudden stop in capital flows is defined as a sudden slowdown in private capital inflows into emerging market economies, and a corresponding sharp reversal from large current account deficits into smaller deficits or small surpluses (Calvo, Guillermo A. (1998). “Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops,” Journal of Applied Economics, 1(1): 35-54.). Sudden stops are usually followed by a sharp decrease in output, private spending and credit to the private sector, and real exchange rate appreciation. The term “sudden stop” was inspired by a banker’s comment on a paper by Dornbusch and Werner about Mexico, that “it is not speed that kills, it is the sudden stop” (Dornbusch, R., I. Goldflam and R.O. Valdés (1995), “Currency Crises and Collapses”, Brookings Papers on Economic Activity, 2, pp. 219-293.).
The second approach identifies variables that help to anticipate statistically 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 $t + 1$ based on a set of explanatory variables observed at $t$. This type of financial crisis analysis looks at pooled panel data employing discrete choice techniques in which macroeconomic and financial data are used to explain discrete crisis events in a range of countries. Eichengreen et al. (1996) adopted a probit model to analyze and predict crises for industrial countries using quarterly data for 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) adopted the logit and multinomial logit models to predict crashes of emerging market currencies 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 early warning signals of financial crises. However, these models are parametrically statistical models, which 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 possible crises at all times. Furthermore, a great deal of data about different variables needs to be collected to construct these models.

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

The main objective of this paper is to develop a preventive model that is able to issue in advance a detecting signal of any problems or tensions on the foreign exchange market.

A recent approach was been developed, it’s based on some emerging computational techniques such as artificial intelligence methods to predict financial crises, based upon some 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 foreign exchange 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 of Southeast Asia economies using some currency volatility indicators. Celik and Karapete (2007) used a feedforward neural network (FFNN) model for forecasting banking crisis and produced 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 indicators. Usually, the randomness of indicators selection often leads to some unexpected results. That is, different indicator selections will lead to different prediction results.

This study proposes empirical mode decomposition based learning which is a new learning paradigm combined with neural networks for financial crisis forecasting.

The neural network used in this study is the back-propagation algorithm, a popular tool for pattern recognition. In a sense, the process of building a financial crisis early-warning system or a financial crisis forecasting model is actually transformed into a pattern recognition problem.

V. Methodology Formulation

V.1. Overview of Neural Networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. Figure 2 illustrates a neural network structure as defined by the various previous works:

ANNs, learn by example. 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 model is back-propagation neural network (BBNN) that uses back-propagation learning algorithm. 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 possible minimizing of estimation error function. The algorithm can be first trained by the in-sample dataset and then applied to out-of-sample dataset for prediction. This ability to learn from examples and the ability (based on this learning) to generalize to new situations is the most attractive feature of the neural network paradigm. Basically, the final output of the BPNN-based forecasting model can be summarized as:

The network receives the information on 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 $\alpha$ and transformed by the activation function $Q$. We obtain a new set of variables $h_1, h_2, \ldots, h_n$, so that:

$$h_j = Q(\alpha_0 + \sum_{i=1}^{n} \alpha_{ij} X_i) \quad (1)$$

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

$$Y_k = F[\beta_0 + \sum_{j=1}^{m} \beta_{jk}(h_j)] \quad (2)$$

Where:

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

The main reason for selecting BPNN as a predictor is that a BPNN is often viewed as a universal approximator. Hornik et al. (1989) found that a three-layer BPNN with an identified transfer function in the output unit and logistic functions in the middle-layer units can well approximate arbitrarily any continuous function, given a sufficient amount of middle-layer units. That is, 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 to give to the network a large number of examples for which the input and output associated are known and weights are modified to correct the error committed by the network (i.e. the difference between the desired and the obtained responses). Thus learning is seen as an optimization problem of finding the network coefficients for minimizing a cost
function. The most used cost function is the squared function on the base of learning; it is to minimize the sum of squared errors between the network output and the real value of the output.

One of the major ANN advantages is that their learning algorithms are applicable to all networks types. We have all the freedom as regards the choice of the best adapted architecture to the problem, and whatever the network structure we can always use the same set of learning algorithms. This flexibility allows implementation including networks whose architecture depends strongly on the structure of the problem to model expressed by equations.

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

V.2. An Overview of the EMD System

Huang et al. (1998, 1999) developed the Hilbert-Huang transformation\(^3\) (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 functions (IMF), each of them representing an embedded characteristic oscillation on a separated time-scale. An IMF is defined by two criteria: i) the number of extrema and 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 zero. The first criterion is almost similar to the narrow band requirement of a Gaussian process, while the latter condition modifies a global requirement to a local one, and if necessary to ensure the instantaneous frequency. In other words, the EMD is based on the direct extraction of energy associated with various intrinsic time scales.

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

The starting point of the empirical mode decomposition (EMD) 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 (say, 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 terminating at the two minima and

http://keck.ucsf.edu/~schenk/Huang_etal98.pdf
passing through the maximum which necessarily exists between them. For the picture to be complete, one still has to identify the corresponding (local) low-frequency part \( t^{-} \leq t \leq t^{+} \). Assuming that this is done in some proper way for all the oscillations composing the entire signal, the procedure can then be applied on the residual consisting of all local trends, and 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 \( e_{\text{min}}(t) \) (respectively, \( e_{\text{max}}(t) \);
3- Compute the mean \( m(t) = (e_{\text{min}}(t) + e_{\text{max}}(t))/2 \);
4- Extract the detail \( d(t) = x(t) - m(t) \);
5- Check the properties of \( d(t) \):
   a. If it is an IMF, denote \( d(t) \) as the \( i^{\text{th}} \) IMF and replace \( x(t) \) with the residual \( r(t) = x(t) - d(t) \). The \( i^{\text{th}} \) IMF is often denoted as \( c_{i}(t) \) and the \( i \) is called its index;
   b. If it is not, replace \( x(t) \) with \( d(t) \);
6- Repeat steps 1 to 5 until the residual satisfies some stopping criterion.

One stopping criterion proposed by Huang et al. (2003) for extracting an IMF is: iterating predefined times after the residue 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 residue \( r(t) \) becomes so small that it is less than the predetermined value of a substantial consequence, or when the residue \( r(t) \) becomes a monotonic function from which no more IMFs can be extracted. The original time series can be expressed as the sum of some IMFs and a residue:

\[
x(t) = \sum_{i=1}^{N} c_{i}(t) + r(t) \tag{3}
\]

Where \( N \) is the number of IMFs, and \( r(t) \) means the final residue.

The advantages of EMD can be briefly summarized as follows: first, it can reduce any 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; third, the IMFs have a clear instantaneous frequency as the derivative of the phase function, so the Hilbert transformation can be applied to the IMFs, allowing us to analyze the data in a time-frequency-energy space.

VI. Empirical Study

VI.1. Data

In order to illustrate and verify the proposed EMD-ANN model, analysis on Republic of Turkey as a country of MENA region is conducted in this study.
The data set used is daily exchange rate data for Turkish exchange rate against the US dollar obtained from the Pacific Exchange Rate Service\(^4\). The main reason for choosing this currency is that this currency is typical representative of MENA region which suffered from the 1994 currencies crisis and 2000-2001 financial and currency crisis. The sample data covers the period from January 1991 to April 2010, with a total of 5036 observations. For purposes of training and testing, the data set is divided into two parts, in-sample and out-of-sample. In-sample goes from 01/01/1991 to 12/07/2002 (3022 observations), used for model building for neural network. Out-of-sample goes from 15/07/2002 to 20/04/2010 (2014 observations), used for validation and test. Figure 2 shows the data series of USD/TRY:

The Turkish economy was been hit by two crises in the last decade. The first one occurred at the beginning of 1994, at which time there was a managed float. In the aftermath of the crisis in 1994, the Turkish economy contracted by 6\%, the highest level of annual output loss in the history of the Turkish Republic. In the first quarter of 1994, the Turkish Lira was devalued 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 to the International Monetary Fund (IMF) by the government, which calmed market pressure. However, at 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) year-end depreciation exchange rate. This unsustainable situation ended on February 19, 2001 when the Prime Minister announced that there was a severe political crisis, which had ignited an equally serious economic crisis in the highly sensitive markets. On that February date, 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.

\(^4\)http://fx.sauder.ubc.ca/
VI.2. Crisis Model

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

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

Where:

- \( \Delta e_{i,t} \) is the deflation rate of nominal exchange rate of currency \( i \) at time \( t \);
- \( \beta \Delta (i_{i,t} - i_{USD,t}) \) is the difference of interest rate between currency \( i \) and American Dollar;
- \( \Delta r_{t,t} \) is the change rate of foreign reserve;
- \( \alpha, \beta, \gamma \) are the weights to make sure that the variances are equal among these three parts.

Kaminsky et al. (1998), Kaminsky (1998), Kaminsky and Reinhart (1999) and Goldstein et al. (2000) followed the concept of Eichengreen et al. (1995, 1996) fairly closely, but they excluded interest rate differentials in their index and comparisons to a reference country. Kaminsky and Reinhart (1999) modified this formula as follows:

\[
EMP = \left( \frac{\Delta e}{e} \right) - \left( \frac{\sigma_e}{\sigma_R} \right) \left( \frac{\Delta R}{R} \right) \quad (5)
\]

Where:

- \( \Delta e/e \) is the rate of change of exchange rate;
- \( \Delta R/R \) is the rate of change of foreign reserves;
- \( \sigma_e \) is the standard deviation of \( \sigma_e/\sigma_R \), and \( \sigma_R \) is the standard deviation of \( \Delta R/R \).

The reason to remove 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 \( \sigma_e/\sigma_R \) is similar to the function of \( \alpha, \beta, \gamma \) to make the variances of each part equal.

However, a major drawback of this approach is that the weights - as well as the threshold value used to identify the speculative attack - are somewhat arbitrary. Kaminsky et al. (1998), for example, define crises as periods in 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 same classification as Kaminsky and Reinhart (1999) did. The currency crises are defined as the situation when the observed EMP is greater than 3 standard deviations, otherwise no currency crisis is said to have happened. A currency crisis can then be defined as follows:

\[
crisis_{t,t} = \begin{cases} 
1 & \text{if } EMP_{t,t} > \mu_{EMP_{t}} + 3\sigma_{EMP_{t}} \\
0 & \text{otherwise}
\end{cases} \quad (6)
\]
Where $\mu_{EMP,t}$ and $\sigma_{EMP,t}$ are calculated based on the in-sample data and used to define the crisis for both the in-sample and out-of-sample data.

**VI.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 typical currency in the MENA region is analyzed by fully EMD-ANN procedure. The data set of Turkish Lira is decomposed into some IMCs via the Hilbert-Huang transform technique. Figure 3 presents the decomposed results. From the figure, it is easy to see that the USD/TRY data consists of 10 IMCs and one residue. These IMCs can formulate a basis of the proposed EMD-ANN learning system.

We include IMFs and residue components for final multi-scale learning in the neural model as input variables. 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 signaling a warning that a currency crisis will happen. Otherwise, there is no predicted currency crisis.

The IMFs and the residue derived by applying EMD to the data set are shown in Figure 3. The sifting processes produce 10 IMFs plus one residue for the daily data. All the IMFs are listed in the order in which they are extracted, that is, from the highest frequency to the lowest frequency; the last one is the residue.

All the IMFs present changing frequencies and amplitudes, which is not the same with any harmonic. With the frequency changing from high to low, the amplitudes of the IMFs are becoming larger: for example, all the amplitudes of IMF1 are small but the amplitudes of IMF10 are restricted to only 2. The residue is more slowly varying around the long term average.

From this decomposition, a neural network model analyzes components for final multi-scale learning. The network has eleven neurons on the input layer (corresponding to the 10 IMFs and the residue), and a 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 can guarantee a good generalization on new data.

The next step is the use of IMCs and residue (input data) to train the neural network models. In this step, the first task is to determine the training targets, using Equation 6. Using the IMCs and training targets, the neural network training process is easy to implement. The final step is to test the trained neural network for verification purpose.

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

- Dividing the database into two sets, the training series (60% of data), and testing and validating data (40% of data).
- Values normalization is included in the interval $[-1,1]$.
- Creation of an ANN with one hidden layer with 10 neurons. We chose a sigmoid hyperbolic tangent transfer function (tansig).
- The learning function is Gradient Descent with momentum term (traingdm).

---

5 We determined the neural network parameters after a large number of tests since there is no general rule that can easily define these parameters.
The number of iterations is 10000 epochs, the learning rate is 0.3, and the convergence rate is 0.6.

Figure 3. Empirical Mode Decomposition of USD/TRY

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 whose the values are between zero and one. We have already defined a threshold and when the output reaches this threshold, a signal of crisis is emitted.

VI.4. Results

The assessment of performance of warning crisis tool is traditionally based on two measures (coverage and confidence), which can be defined from the following matrix:

<table>
<thead>
<tr>
<th></th>
<th>Crisis</th>
<th>No Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>No Signal</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>

Knowing that A is the number of good signals, B is the number of false signals, C the number of false silences and D the number of good silence.

The coverage corresponds to the percentage of crises correctly predicted:

\[
Coverage = \frac{A}{A + C}
\]

Confidence is the probability of having a real crisis when a signal is emitted:

\[
Confidence = \frac{A}{A + B}
\]

Table 1 presents the performance obtained (coverage and confidence):

<table>
<thead>
<tr>
<th></th>
<th>Crisis</th>
<th>Non Crisis</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Non signal</td>
<td>0</td>
<td>5031</td>
<td>5031</td>
</tr>
<tr>
<td>Total</td>
<td>3</td>
<td>5033</td>
<td>5036</td>
</tr>
<tr>
<td>Coverage</td>
<td></td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Confidence</td>
<td></td>
<td>60%</td>
<td></td>
</tr>
</tbody>
</table>

The performance obtained using neural networks are excellent for forecasting horizon and confidence is about 60%. This means that when a signal is issued, a crisis actually occurs 2 times out of 3. This high confidence is associated with significant coverage, which allows us to cover 100% of crises. This implies that the proposed EMD-ANN learning approach is a very promising alternative solution for currency crisis forecasting.

To summarize, it is clear that the overall accuracy for these cases is quite promising for data set. This implies that the two patterns (indicating crisis and not indicating crisis) in the 1994, November 2000 and February 2001 financial crises periods are captured successfully and support our claim that crisis-related data are usually
classified easily. However, there is still some problem is the results: the model even emitted two false signals, but in sum, the results obtained are quite satisfactory.

So, the proposed EMD-ANN tool performs well. The main reason is that the EMD produces some IMCs with different scales, making the difficult problem simple. Furthermore, different IMCs with different scales include different information and, therefore, neural networks can extract more knowledge, thereby increasing the generalization ability of neural networks.

**VII. Conclusion**

There is a wide agreement among financial economists and policy makers that in order to avoid the devastating damage on the economy due to the currency crisis, we need to have an effective early warning system. Thus, we have tried, in this paper, to build such an early warning system by using the EMD-ANN technique.

Two techniques, neural networks and empirical mode decomposition, have shown their ability to adapt the complex field of currency crisis. Neural networks are, particularly, an outstanding performance, but the "black-box" effect could be regarded as a major drawback due to the fact that it does not give any explanation of the results. This, therefore, justifies the use of the empirical mode decomposition technique which is may be less efficient but easily understood. In fact, this technique can maintain both a stylized representation of crisis mechanisms and integrate strong effects of non-linearity in the causal chains. The empirical results show that EMD-ANN model could provide accuracy rate which as high as 60% for the data set.

In another perspective, and if we suppose that a database of different crisis indicators is available, we will be able to construct a knowledge base which provides more detailed causal relationship among the variables, suggesting concrete policies for increasing the chances of avoiding the crisis. These relationships can also be the basis for theoretical modifications of the modelling approach for further research.

In summary, the work in hand proposes the main following contribution: we have tried to expect only chances of occurrence of currency crisis, and we have provided an alternative to deal with the inherent non-linearities of this problem. This work, however, has a drawback and is due to the fact that it could not provide any economic explanation of the crisis and could not detect which economic indicators are responsible of such crisis. That is because we did not use any explanatory economic or financial indicator in our empirical study. In fact, our main objective in this study was only to develop a model that could serve as a warning system of a crisis.

Finally, a general approach to uncovering the relationships among the variables inductively can be the basis for further hypothesis testing regarding important explanatory factors for currency crises. An important area of future application could be banking and even broader financial crises.
References


