Currency Crisis Forecasting with a Multi-Resolution Neural Network Learning Approach

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Abstract

In this study, an empirical mode decomposition (EMD) based multi-resolution neural network learning paradigm via Hilbert-Huang transform (HHT) is proposed to predict currency crisis for early-warning purpose. In the proposed learning paradigm, the original currency exchange rate series are first decomposed into various independent intrinsic mode components (IMCs) with a multi-resolution Hilbert-EMD algorithm. Then these IMCs with different scales are input into an artificial neural network (ANN) for training purpose. Using the trained ANN, the future currency crisis conditions can be predicted based on the historical data. For verification, two typical currencies — South Korean Won and Thai Baht — are used to test the effectiveness of the proposed multi-resolution neural learning paradigm.

Keywords: Artificial neural networks, empirical mode decomposition, multi-resolution learning, currency crisis forecasting

1 Introduction

During the 1990s, many emerging markets, such as Latin American and Southeast Asian economies, have experienced several episodes of currency crises [1]. Notable examples include the December 1994 devaluation of the Mexican peso and the October 1997 Asia financial turmoil after the devaluation of the Thai baht. These unprecedented and peculiar crises brought large change not only to their economy but also to their society, and since then much attention has been focused on study of the currency crisis from the theoretical and empirical perspectives [1-5]. The main reason of this research stream is that financial practitioners have different purposes about currency crisis analysis. For example, macro policymakers are interested in leading indicators of pressure on exchange rate parties; market participants are increasingly concerned to measure and limit their risk to large currency exchange rate fluctuation; and financial regulators are keen to understand the currency exchange rate exposures of the institutions they supervise.

In the currency crisis analysis, it is important to be clear exactly how a currency crisis is defined. Much relevant literature looks at crisis indices (termed currency pressure indicators) defined as weighted sums of percentage change in exchange rates, interest rates and foreign currency reserves [5]. Use of such indices is appropriate if one views crises from the view of a macro policymaker and is equally interested in "successful" and "unsuccessful" speculative attacks. From the viewpoint of an investor, manager of foreign reserve positions or a macro policymaker who cares primarily about a "successful attack" on the currency, it is more appropriate to consider a simpler definition of currency crisis based on large depreciations of currency exchange rates. To distinguish our research from those of studies which employ currency pres-sure indicators, a large devaluation of currency which far exceeds previous devaluations is defined as a currency crisis event.

In order to detect a currency crisis as soon as possible, many attempts have been done via different currency crisis forecasting models and early warning systems. Generally, there are four types of currency crisis modeling model. The first type is to use structural models to analyze the currency crisis. There are case studies into specific devaluation episodes, often employing explicit structural models of balance of payments crises. Typical examples include Blanco and Garber [6], Cumby and van Wijnbergen [7], Jeanne and Masson [8], and Cole and Kehoe [9]. These studies are informative about the episodes in question and revealing with regard to structural model proposed by theorists [5].

The second type of currency crisis modeling is signal approach. Typical examples include Kaminsky et al. [2], Berg and Pattillo [10], and Kaminsky and Reinhart [11]. In these models, single variables such as real effective exchange rate or debt to GDP levels are considered as a "signal" that a country is potentially in a crisis state when they exceed a specified threshold. While intuitively appealing, signal models are essentially univariate in nature. Kaminsky [12] suggested a combined signal approach to form a composite index for prediction purposes, but this does not solve all problems. For example, suppose that some of the signal variables are very closely correlated. They may each have a very high noise-to-signals 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 [1].

The third type is to use pooled panel data and employ discrete choice techniques to explain discrete crisis events in a range of countries with macroeconomic and financial data. For example, Kumar et al. [5] utilized a logit model to predict emerging market currency crashes. While Echengreen et al. [13] adopted a probit model to analyze and predict the crisis for industrial countries using quarterly data between 1959 and 1993. Similarly, Berg and Pattillo [10] also used a probit model to predict the currency crisis. However, these models are parametrically statistical models, which include several statistical assumptions and have weak robustness. Since a currency crisis is a rare event with nonlinear characteristics, it is difficult for these statistical models to capture the all possible crises for all the time. Furthermore, a great deal of data about different variables must be collected to construct these models [1].

The fourth or final type is to employ some emerging artificial intelligent (AI) technique to predict the financial crisis state. Yu et al. [1] is a typical example. Their study is to utilize some typical technical indicators and a general regression neural network (GRNN) to predict the possible currency crisis. But it is worth noting that the randomness of indicators selection often leads to some unexpected results. That is, different indictors will lead to different prediction results.

For these reasons, this paper attempts to develop an empirical mode decomposition (EMD) based multi-resolution neural network learning paradigm via Hilbert-Huang transform (HHT). In the proposed learning paradigm, the original currency exchange rate series are first decomposed into various independent intrinsic mode components (IMCs) with a multi-resolution Hilbert-EMD algorithm. These different IMCs represent various factors affecting currency fluctuations. Therefore the IMCs are considered as the independent variables for constructing a currency crisis forecasting model. Then these IMCs with different scales are input into an artificial neural network (ANN) for training purpose. Using the trained ANN, the future currency crisis conditions can be predicted based on the historical data. To verify the effectiveness of the proposed currency crisis forecasting approach, two typical currencies — South Korean Won and Thai Baht — are used as the testing targets.

The main motivation of this study is to develop an EMD-based multi-resolution ANN learning approach to constructing an early-warning system of currency crisis. The rest of the study is organized as follows. Section 2 describes an EMD-based ANN learning approach to currency crisis forecasting in detail. For illustration purposes, two typical currencies including South Korean Won and Thai Baht are used for testing purpose in Section 3. Section 4 concludes.

2 A Multi-Resolution Neural Network Learning Approach

2.1 Empirical Mode Decomposition (EMD)

The empirical mode decomposition (EMD) method first proposed by Huang et al. [14] is a form of adaptive time series decomposition technique using spectral analysis via Hilbert-Huang transform (HHT) for nonlinear and nonstationary time series data. Traditional forms of spectral analysis, like Fourier, assume that a time series (either linear or nonlinear) can be decomposed into a set of linear components. As the degree of nonlinearity and nonstationarity in a time series increases, the Fourier decomposition often produces large sets of physically meaningless harmonics when applied to nonlinear time series [15]. For wavelet analysis, it needs to select a filter function beforehand [16], which is difficult for some unknown time series. Naturally, a new spectrum analysis method, EMD based on Hilbert-Huang transform, is emerged.

The basic principle of EMD is to decompose a time series into a sum of intrinsic mode components (IMCs) with the sequel sifting procedure.

(1) Identify all the local extrema including local maxima and minima of $x(t)$,
(2) Connect all local extrema by a cubic spline line to generate its upper and lower envelopes $x_{up}(t)$ and $x_{low}(t)$.
(3) Compute the point-by-point envelope mean $m(t)$ from upper and lower envelopes, i.e., $m(t) = \left(x_{up}(t) + x_{low}(t)\right)/2$.
(4) Extract the details, $d(t) = x(t) - m(t)$.
(5) Check the properties of $d(t)$: (i) if $d(t)$ meets the above two requirements, an IMC is derived and replace $x(t)$ with the residual $r(t) = x(t) - d(t)$; (ii) if $d(t)$ is not an IMC, replace $x(t)$ with $d(t)$.
(6) Repeat Step (1) – (5) until the residual satisfies the following stopping condition: $\sum_{t=1}^{T}\left(d_j(t) - d_{j+1}(t)\right)^2 / d_j^2(t) < SC$, where $d_j(t)$ is the sifting result in the jth iteration, and SC is the stopping condition. Typically, it is usually set between 0.2 and 0.3.

The EMD extracts the next IMC by applying the above procedure to the residual term $r_1(t) = x(t) - c_1(t)$, where $c_1(t)$ denotes the first IMC. The decomposition process can be repeated until the last residue $r(t)$ only has at most one local extremum or becomes a monotonic function from which no more IMCs can be extracted. A typical sifting process can be shown in Figure 1.

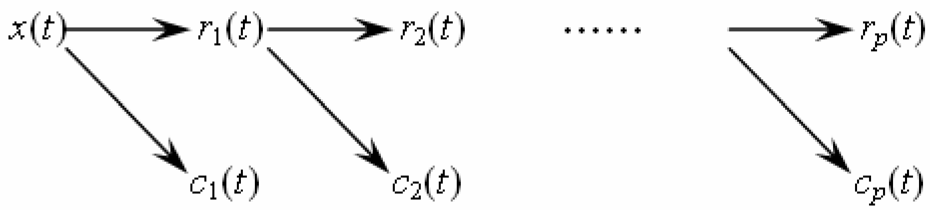

Figure 1. A typical EMD sifting process

At the end of this sifting procedure, the time series $x(t)$ can be decomposed as

$$x(t) = \sum_{j=1}^{p} c_j(t) + r_p(t) \quad (1)$$

where p is the number of IMCs, $r_p(t)$ is the final residue, which is the main trend of $x(t)$, and $c_j(t)$ (j = 1, 2, …, p) are the IMCs, which are nearly orthogonal to each other, and all have nearly zero means. Thus, one can achieve a decomposition of the data series into m-empirical modes and a residue. The frequency components contained in each frequency band are different and they change with the variation of time series $x(t)$, while $r_p(t)$ represents the central tendency of time series $x(t)$.

2.2 The EMD-based Multi-Resolution Neural Network Learning Approach

As known to all ANNs are a new kind of intelligent learning algorithm and are widely used in many practical problems [17]. However, a major challenge in neural network learning is how to make the trained networks possess good generalization ability, i.e., they can generalize well to cases that were not included in the training set. Some researchers argued to use the cross-validation technique for getting good generalization [18]. But in the cross-validation technique, neural network learning is based on a single series representation for the entire training process. However, when the problem is very difficult and complex, single series representation for neural network learning may be inadequate [19]. For this reason, the EMD-based multi-resolution neural network learning is employed to decompose a time series and approximating it using decomposed components via a multi-variable analysis framework. Generally speaking, the EMD-based multiscale neural learning paradigm consists of three steps.

Step I: Data Decomposition. The original time series are decomposed into various independent IMCs with a range of frequency scales. These produced different IMCs can formulate the inputs of neural networks. Figure 2 presents an illustrative decomposition example of a time series with p IMCs and one residue.

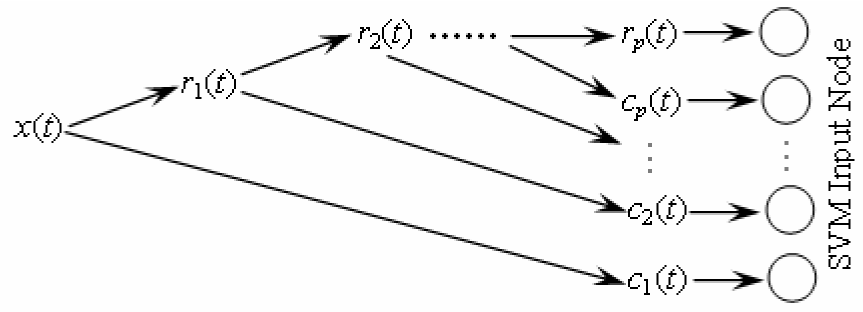

Figure 2. Data decomposition based on EMD

Step II: ANN Training. Once the input patterns are determined, the ANN training can be started. In this study, the architecture of ANN is composed of (p+1) input neurons (p+1 IMCs by data decomposition step), $2(p+1) \pm 1$ hidden neurons (in terms of trial and error), one output neurons. The ANN training process is performed by Matlab software package.

Step III: Crisis Prediction. After training the ANN, we can use the trained ANN to predict the future currency crisis conditions for out-of-sample data in the final step. In terms of above steps, we classify the currency crisis conditions. When an unknown vector with (p+1) dimensions is input, the one with the highest output value is to be picked as the final ANN output, i.e., the pattern to which the given currency crisis condition belongs. Particularly, output "0" is classified as non-crisis pattern, while output "1" is classified as crisis pattern, implying the currency crisis condition might be trapped in a crisis period.

In order to verify the effectiveness of the proposed EMD-based ANN approach to currency crisis forecasting, two typical Asian currencies — South Korean Won and Thai Baht, which are suffered from the 1997 disastrous currency crisis experience, are used as testing targets.

3 Experiment Analysis

3.1 Data Description and Experiment Design

In our empirical analysis, we set out to examine the currency crisis condition. As earlier noted, a currency crisis event is defined as a large devaluation of currency which far exceeds previous devaluations. From this definition and some previous studies (e.g. [5]), a crisis can be defined as an abnormal event where rate of change (ROC) of exchange rate ($ROC_t = (e_t - e_{t-1})/ e_{t-1}$) exceeds an extreme value:

$$\text{Crisis} = \begin{cases} 1, \text{ if } ROC > \mu_{ROC} + 2.5\sigma_{ROC}, \\ 0, \text{otherwise.} \end{cases} \tag{2}$$

where crisis = 1 represents the occurrence of currency crisis, μ_{ROC} and σ_{ROC} are the sample mean and sample standard deviation of the ROC respectively. A crisis is said to occur when the ROC is more than 2.5 standard deviations above the mean. Although the choice of 2.5 as a threshold value is somewhat arbitrary, the cataloging of crises obtained by this method tends to follow closely the chronology of currency market disruptions described in the literature [2, 11]. From Equation (2), the main task of crisis forecasting model is to judge whether the currency crisis occurs or not. Therefore two patterns, i.e., crisis occurrence and un-occurrence, will be recognized. Note that currency rates against the US dollar are specified in advance.

The data used in this study are daily exchange rate data for two currency exchange rates against the US dollar (South Korean won, Thai baht) and are obtained from the Pacific Exchange Rate Service (http://fx.sauder.ubc.ca/). The main reason for choosing these two currencies in this study is that these two currencies are typical representatives suffered from the 1997 disastrous currencies crisis experience. Particularly, our sample data span the period from January 2, 1996 to December 31, 1998 with a total of 755 observations. For purposes of training and testing, we take daily data from January 2, 1996 to December 31, 1997 as in-sample (training periods) data sets

(506 observations). We also take data from January 2, 1998 to December 31, 1998 as out-of-sample (testing periods) data sets (249 observations), and these are used to evaluate the good or bad performance of our currency crisis prediction. In order to save space, the original data are not listed and can be obtained from the website.

To evaluate the forecasting ability of the proposed EMD-based multi-resolution ANN approach, we select some popular forecasting methods from the existing literature – such as logit model [5], probit model [4], signal approach [2, 4], GRNN model [1] – for comparative purposes. In addition, we also compare the forecasting performance with two typical discriminant analysis models, i.e., linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). LDA can handle the case in which the within-class frequencies are unequal and its performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set, thereby guaranteeing maximal separability. QDA is similar to LDA, only dropping the assumption of equal to be a quadratic surface (e.g. ellipsoid, hyperboloid, etc.) in the maximum likelihood argument with normal distributions. Interested readers can refer to Hair et al. [20] for more details. For LDA, a linear discriminant function can be written as

$$L(X) = \mathbf{A}X^T \quad (3)$$

and a quadratic discriminant function can be represented by

$$Q(X) = \mathbf{A} + \mathbf{B}X^T + X\mathbf{K}X^T \quad (4)$$

where **A**, **B**, **K** are coefficients to be estimated. Note that the independent variable ***X*** is composed of IMCs obtained via EMD in these two discriminant analysis approaches. Finally, the classification accuracy is used to measure the prediction performance of the proposed approach.

3.2 Experiment Results

In this subsection, a detailed process of the proposed approach is first presented via the testing examples. Then we report classification results for the training data and testing data. For further comparison, the results for different models are also provided.

3.2.1 Methodology implementation process

Using the proposed approach, the first step is that the two typical currency rates are decomposed into some IMCs via Hilbert-Huang transform technique. Figures 3 and 4 present the decomposed results for South Korean Won (KRW) and Thai Baht (THB). From the figure, it is easy to find that the KRW data consists of 9 IMCs and one residue, while THB data are composed of 7 IMCs and one residual. These IMCs can formulate a basis of the proposed EMD-based multi-resolution ANN learning paradigm.

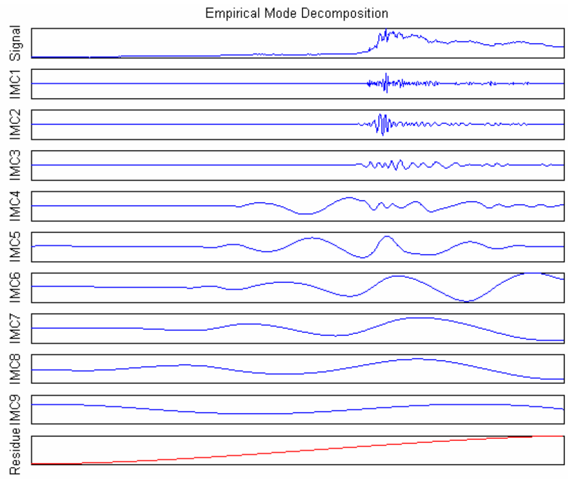

Figure 3. EMD decomposition results of KRW

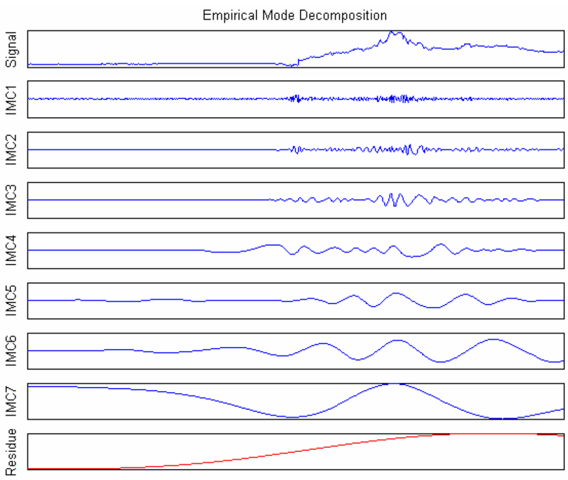

Figure 4. EMD decomposition results of THB

The second step is to utilize the IMCs to training the ANN models, i.e., ANN training. In this step, the first work is to determine the training targets. Using Equation (2), the training targets can be obtained. Using the IMCs and training targets, the ANN training process are easy to be implemented.

The third step is to apply the trained ANN to testing exemplars for verification purpose. With the three-step process, the proposed EMD-based multi-resolution ANN learning approach is easy to be carried out.

3.2.2 Forecasting results on in-sample data

As earlier indicated, the 1996-1997 exchange rates data are used as the training samples for training purpose. Accordingly, the forecasting results based on in-sample data are shown in Tables 1-2.

Table 1. Classification results for Korean Won

Patterns	Occurrence	No Occurrence	Total
Occurrence	10 (100%)	0 (0%)	10
No Occurrence	0 (0%)	496 (100%)	496
Total	10	496	506

Table 2. Classification results for Thai Baht

Patterns	Occurrence	No Occurrence	Total
Occurrence	6 (100%)	0 (0%)	6
No Occurrence	0 (0%)	500 (100%)	500
Total	6	500	506

From Tables 1-2, we can find two distinct features. On the one hand, the two patterns of the currency crisis can be classified correctly in all testing cases. In particular, the accuracy in classifying two patterns is very high in the two cases. The classification accuracy arrives at 100%. This implies that the proposed EMD-based multi-resolution ANN learning approach is a very promising alternative solution to currency crisis forecasting. On the other hand, there will have a potential problem for 100% classification accuracy of the two cases. If the training is not sufficient, the crisis-trained ANN model may lead to the overfitting problem. The question of how to avoid ANN overfitting is still a conflicting issue and it is worth exploring further. To avoid the possible overfitting problem, cross-validation techniques, such as *k*-fold and leave-one-out are often suggested.

To summarize, it is clear that the overall accuracy for all two cases is quite promising for the training data. This implies that the two patterns (crisis occurrence and crisis un-occurrence) in the 1997 financial crisis period (training data) are captured successfully and support our claim that crisis-related data are usually easily classified. In order to test the effectiveness of the proposed multi-resolution ANN model, out-of-sample verification is necessary.

3.2.3 Forecasting results on out-of-sample data

To verify the effectiveness of the proposed currency crisis forecasting approach, we take the data from January 2 1998 to December 31, 1998 as the out-of-sample data (249 observations). This is a distinct feature of our study, which differs from many previous studies in that we focus on the degree to which currency crises can be predicted. Earlier studies take a more descriptive approach, relating the occurrence of crises to contemporaneous rather than lagged variables. Studies which have attempted to predict crises have mostly assessed their results on an “in-sample” basis. In contrast, we evaluate the predictions on an explicitly out-of-sample basis. Applying the crisis-trained EMD-based multi-resolution ANN model, empirical testing is performed. The detailed testing results are shown in Tables 3-4.

Table 3. Classification results for Korean Won

Patterns	Occurrence	No Occurrence	Total
Occurrence	2 (100%)	0 (0%)	2
No Occurrence	7 (2.83%)	240 (97.17%)	247
Total	9	240	249

Table 4. Classification results for Thai Baht

Patterns	Occurrence	No Occurrence	Total
Occurrence	5 (83.33%)	1 (16.67%)	6
No Occurrence	5 (2.06%)	238 (97.94%)	243
Total	10	239	249

From the results shown in Tables 3-4, we can draw the following three conclusions. First of all, the classification accuracy for the out-of sample data is not as good as that for the in-sample data. In general, however, the results obtained are quite satisfactory. Secondly, among the two cases, the total classification accuracy for the Korean Won is 97.19% (242/249) and the accuracy for Thai Baht arrives at 97.59% (243/249). These classification results for testing data also demonstrate the effectiveness of the proposed multi-resolution ANN learning paradigm. Thirdly, as a rare event, financial crisis is difficult to be captured in the economic life. In our study, the proposed approach is rather promising. Finally, one of the main contributions of our results is that the crisis trained multi-resolution ANN model is able to provide an efficient decision sign or an early warning signal about whether the currency fluctuation condition has entered a crisis level.

In sum, application of the crisis-trained EMD-based multi-resolution ANN learning approach to the out-of-sample data shows very accurate classification results in all cases, implies in the sense that the proposed model is worth generalizing into more currencies to predict the currency crisis level.

3.2.4 Results of comparison with other methods

Each of the forecasting models described in the last section is estimated and validated by in-sample data. The model estimation and selection process is then followed by an empirical evaluation, which is based on the out-of-sample data. At this stage, the models' performance is measured using the total classification accuracy for simplicity. Table 5 shows comparison results.

Table 5. Comparisons of forecasting performance for different methods (%)

	LDA	QDA	Signal	Logit	Probit	GRNN	Proposed ANN
KRW	68.67	75.10	79.52	78.31	84.74	92.77	97.19
THB	57.77	63.61	78.95	84.73	87.64	93.82	97.59

From Table 5, we can conclude four aspects: (1) QDA outperforms LDA in terms of the total classification ratio for all tested cases. The main reason for this is that LDA assumes that all classes have equal covariance. In fact, different classes often have different covariances. Thus, heteroscedastic models are more appropriate than homoscedastic ones. (2) Although the signal, logit and probit models yield confused results, their performance is better than that of the LDA and QDA models. One possible reason is that it is easier for the former to capture possible crisis signals. The reasons for the confused results of the three approaches are worth exploring further. (3) Another distinct characteristic of the proposed EMD-based multi-resolution ANN learning approach is that it only depends on one variable. This is distinctly different from previous approaches, such as sign approach, logit and probit models presented in the existing studies. Most previous studies depend on many independent variables, which increase the difficulty of collecting related data. (4) Generally, the EMD-based multi-resolution ANN learning approach is promising, implying that our proposed approach is a competitive forecasting model for currency crisis forecasting among the methods tested.

4 Conclusions

In this paper, an EMD-based multi-resolution ANN learning approach is proposed to currency crisis forecasting using the historical data. Applications of the proposed EMD-based multi-resolution ANN learning approach to out-of-sample data display surprisingly high accuracy in judging each currency crisis level, revealing that the proposed EMD-based multi-resolution ANN learning approach might also be useful for financial practitioners to attempt to build a currency crisis forecasting model or a currency crisis early-warning system. Furthermore, comparing our model with the other forecasting methods, experimental results show that the proposed EMD-based multi-resolution ANN learning approach is superior to the other classification methods in currency crisis prediction, implying that our proposed approach can be used as a promising alternative to currency crisis forecasting.

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