A Hybrid Intelligent Early Warning System for Predicting Economic Crises: The Case of China

Dongwei Su and Xingxing He

Jinan University

11. January 2010

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Dongwei Su
College of Economics
Jinan University
Guangzhou, Guangdong 510632
Email: tdsu@jnu.edu.cn

Xingxing He
College of Economics
Jinan University
Guangzhou, Guangdong 510632
Email: hexingxing@guet.edu.cn

***Abstract*—This paper combines artificial neural networks (ANN), fuzzy optimization and time-series econometric models in one unified framework to form a hybrid intelligent early warning system (EWS) for predicting economic crises. Using quarterly data on 12 macroeconomic and financial variables for the Chinese economy during 1999 and 2008, the paper finds that the hybrid model possesses strong predictive power and the likelihood of economic crises in China during 2009 and 2010 remains high.**

***Index Terms*—Computational intelligence, artificial neural networks, fuzzy optimization, early warning system, economic crises**

I. Introduction

An economy is usually classified as a manifestation of complex social systems. Complex systems are composed of many particles, or objects, or elements that may be of the same or different kinds. The elements may interact in a more or less sophisticated fashion by more or less nonlinear couplings. The trend of complex systems is dynamic, unstable, discontinuous and irreversible with multiple possibilities, rendering it difficult to predict the state of the economy. Investigation into huge amount of multivariate data is needed to extract and manipulate information distributed within the system, so that prediction and decision-making can be soundly sustained.

The existing literature on the predictability of economic crises is constantly expanding. One vein of the literature consists of studies based on a model known as "signals approach" which involves observing the behavior of a number of economic indicators as they issue signals when they exceed certain threshold values. See for example, Kaminsky, Lizondo and Reinhart (1998), Kaminsky and Reinhart (1999), Goldstein, Kaminsky and Reinhart (2000), Alvarez-Plata and Schrooten (2004) and Peng and Bajona (2008). A second vein of literature focuses on parametric structural models, including logit or probit models, and uses lagged values of early warning economic indicators to predict crises. See for example, Frankel and Rose (1996), Berg and Pattillo (1999), Kim and Moon (2001), Komulainen and Lukkarila (2003), Kumar, Moorthy and Perraudin (2003), Beckmann, Menkhoff and Sawischlewski (2006), Kalotychou and Staikouras (2006) and Bussiere and Fratzscher (2006). A third vein of the literature utilizes techniques of computational intelligence, such as artificial neural networks (ANN), fuzzy logic systems and genetic algorithms, and artificial intelligence and machine learning. See for example, Kim, Oh, Sohn and Hwang (2004), Niemira and Saaty (2004), Kim, Hwang and Lee (2004), Pang and Feng (2006), Yu, Lai and Wang (2006), Celik and Karatepe (2007), and Sohn, Oh, Kim and Kim (2009).

Although extant research is useful in understanding the origin of economic crises, more work needs to be done to better predict future crises. The complexity and dynamics of real-world economic problems require more sophisticated analytical methods and techniques. The purpose of this paper is to build a hybrid intelligent early warning system (EWS) which can deal more powerfully with issues like fast-learning, uncertainty, adaptability, vulnerability, knowledge capability, and hierarchical solution, etc.

II. A Hybrid Intelligent EWS

Our hybrid intelligent EWS for economic crises consists of the following three components: The first component utilizes time-series econometric models to form forecasts of key economic indicators. The second component relies on fuzzy optimization to assess various types of macroeconomic and financial risks. The third component predicts the likelihood of economic crises based on ANN. Figure 1 presents the overall framework of our hybrid intelligent EWS model.

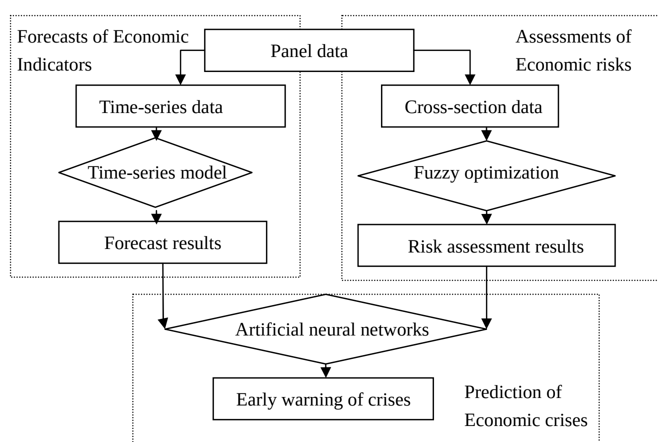

Fig. 1. The framework of a hybrid intelligent EWS model

A. Forecasts of Economic Indicators with Time-series Models

We use autoregressive integrated moving average (ARIMA) models to form individual forecasts of 12 time-series macroeconomic and financial indicators. ARIMA models are, in theory, the most general class of parametric models for forecasting difference-stationary time-series variables. In fact, ARIMA models are fine-tuned versions of random walk and stochastic trend models—the fine-tuning consists of adding lags of the differenced series and/or lags of the forecast errors to the prediction equation so that any last traces of autocorrelation from forecast errors are removed. The general formula for ARIMA models is as follows:

$$\Phi(B)\nabla^d x_t = \Theta(B)e_t \qquad (1)$$

where $\Phi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$, B is the backward operator, ∇ is the difference operator, d is the rank of differences, x_t represents time-series variables, $\Theta(B) = 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q$, and e_t is a white-noise disturbance term.

B. Risk Assessment Using Fuzzy Optimization

We set up a fuzzy optimization model to assess various macroeconomic and financial risks.[1] Suppose that an intelligent EWS consists of n groups of cross-section observations, and that each optimal set of cross-section observations contains m early-warning economic indicators, i.e., the domain of discourse is denoted by $X = x_1, x_2, ..., x_n$. The data matrix for the EWS indicators is as follows:

$$\begin{pmatrix} X_{11} & X_{12} & ... & X_{1n} \\ X_{21} & X_{22} & ... & X_{2n} \\ ... & ... & ... & ... \\ X_{m1} & X_{m2} & ... & X_{mn} \end{pmatrix} = (X_{ij})$$

where X_{ij} is the value of the ith EWS economic indicator at the jth time period, $i = 1, 2, ..., m, j = 1, 2, ..., n$.

For EWS indicators that are positively related to economic risks, we apply the following formula to compute its relative membership grade r_{ij}:

$$r_{ij} = \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (i = 1, 2, ..., m) \qquad (2)$$

For EWS indicators that are negatively related to economic risks, r_{ij} is computed using the following formula:

$$r_{ij} = \frac{\max(X_i) - X_{ij}}{\max(X_i) - \min(X_i)} \quad (i = 1, 2, ..., m) \qquad (3)$$

Using equation (2) and (3), we transform the data matrix (X_{ij}) into the following matrix of relative membership grade (R_{ij}):

$$R = \begin{pmatrix} r_{11} & r_{12} & ... & r_{1n} \\ r_{21} & r_{22} & ... & r_{2n} \\ ... & ... & ... & ... \\ r_{m1} & r_{m2} & ... & r_{mn} \end{pmatrix}$$

where $0 \leq r_{ij} \leq 1$, $i = 1, 2, ..., m$, $j = 1, 2, ..., n$.

[1]See Kasabov (1996) for a comprehensive presentations of fuzzy theory.

Denote the largest and the smallest risk-based relative membership grade as $g = (g_1, g_2, ..., g_{12})' = (1, 1, ..., 1)'$ and $b = (b_1, b_2, ..., b_{12})' = (0, 0, ..., 0)'$, respectively. Using fuzzy optimization theory, we compute the general risk-based relative membership grade at time j as follows:

$$u_j = \frac{1}{1 + \Sigma_{i=1}^m [w_i(g_i - r_{ij})]^2 / [w_i(r_{ij} - b_i)]^2} \qquad (4)$$
$$(j = 1, 2, ..., m)$$

where u_j is the relative degree of economic risk and w_i is the weight for the ith EWS indicator. A high value of u_j indicates a high level of economic risks.

C. An Intelligent EWS Based on ANN

Using output data from ARIMA forecasts and risk assessments, we establish an ANN model to predict the likelihood of economic crises. ANNs are multivariate nonlinear nonparametric statistical methods that try to simulate the structural and/or functional aspects of biological neural networks. They represent an adaptive system composed of many simple processing elements that change their structure to reflect external or internal information that flows through the network during the learning phase. ANNs are particularly suitable for function approximation, forecasting and pattern recognition where the (economic) relationships among variables are not known from the theory or are difficult to specify.[2]

This paper utilizes the most widely used ANN model called Back-Propagated Delta Rule Networks (BP), where all the nodes and layers are arranged in a feed-forward manner (see Figure 2). The first layer is called the input layer, where the information is received in the ANN. Usually the input layer consists of as many input nodes as there are independent variables. The last layer is called the output layer where the ANN produces its solutions. In-between the input and output layers, there are one or more hidden layers.

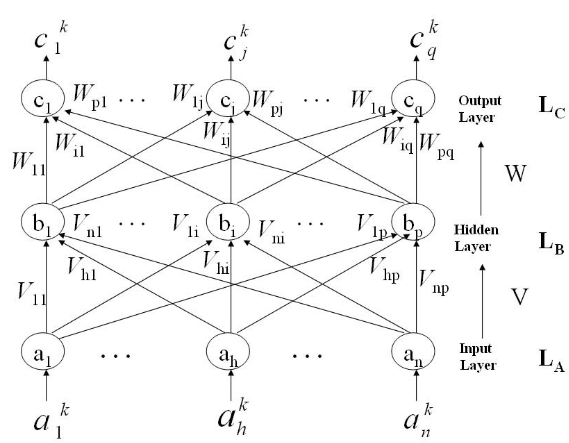

Fig. 2. Topological structure based on the BP neural networks

BP is a generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer

[2]See McNelis (2005) for a comprehensive presentation of ANNs.

function. Input vectors and the corresponding target vectors are used to train a network until the differences between the ANN output values and the known target values are minimized. Network with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Standard BP uses a gradient descent algorithm, as does the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. After the ANN is trained, its forecasting ability can be tested on another sample.

III. An Empirical Analysis Based on Chinese Data

A. The Selection and Standardization of Economic Indicators

A pair of economic variables frequently appear in the EWS literature are the level of net export and foreign reserves. These two variables are used as an indicator of the current account condition. For example, declining volume of exports can be considered as an indication of competitiveness loss of a country, possibly caused by an overvalued domestic currency. In this paper, we use net export as a fraction of GDP, foreign reserve as a fraction of GDP, FDI as fraction of GDP, foreign debt as a fraction of GDP, the ratio of FDI and foreign debt and the real exchange rate to proxy for balance-of-payment conditions. Another set of important economic and financial indicators are inflation rate, real interest rate and the growth rate of money supply. In particular, the growth rate of M1 and M2 can point to whether there is excess liquidity in the monetary system. A high money growth rate may invoke speculative attacks on the domestic currency, thus leading to banking and currency crises.

TABLE I presents 12 key economic and financial variables used in this paper together with their predicted signs. A variable is predicted to have a positive sign if it is positively related to the level of economic risks. In this case, the variable is standardized using equation (2). On the other hand, a variable is predicted to have a negative sign if it is negatively related to the level of economic risks. In this case, the variable is standardized using equation (3). All data are of quarterly frequency during 1999 and 2008 with a total of 40 observations for each economic indicators.

TABLE I
Key EWS indicators and their predicted signs

Economic indicator	Predicted sign
Real interest rate	positive
Inflation rate	positive
Real exchange rate	positive
FDI/Foreign debt	positive
Debt/GDP	positive
FDI/GDP	positive
Real GDP growth rate	negative
M2 growth rate	negative
Net export/GDP	negative
Foreign exchange reserves/GDP	negative
Fiscal balance/GDP	negative
Stock-market index	negative

B. Weights of Economic Indicators

We assign different weights for economic indicators based on their perceived level of economic and financial risks: Real GDP growth rate $\succ$ M2 growth rate $\sim$ Real interest rate $\sim$ Inflation rate $\succ$ Real exchange rate $\succ$ FDI/Foreign debt $\succ$ Net export/GDP $\succ$ Foreign exchange reserves/GDP $\sim$ Debt/GDP $\sim$ FDI/GDP $\succ$ Fiscal balance/GDP $\succ$ Stock-market index, where ”$\succ$” means ”higher than” and ”$\sim$” means ”is equivalent to”. We use Analytic Hierarchy Process (AHP) to obtain weights for each economic indicators. TABLE II presents the AHP results.

TABLE II
The weights of key EWS indicators

Economic indicators	Weight
Real interest rate	0.1208
Inflation rate	0.1208
Real exchange rate	0.0989
FDI/Foreign debt	0.0810
Debt/GDP	0.0543
FDI/GDP	0.0543
Real GDP growth rate	0.1476
M2 growth rate	0.1208
Net export/GDP	0.0663
Foreign exchange reserves/GDP	0.0543
Fiscal balance/GDP	0.0444
Stock-market index	0.0364

C. Time-series Forecasts of Economic Indicators

We use ARIMA(p, l, q) models to predict time-series behavior of each economic indicators in 2009 and 2010, using quarterly data between 1999 and 2008. ARIMA modeling involves the following steps: (i) Conduct Dickey-Fuller and Phillips-Perron tests and examine the stationarity of all time-series variables; (ii) If an economic indicator is integrated of order l, difference the time-series variable l times till it becomes stationary; (iii) Identify the number of lags p and q by calculating autocorrelation coefficients and partial autocorrelation coefficients; (iv) Using maximum likelihood estimation and data during 1999 and 2008, obtain the unknown parameter estimates for ARIMA(p, l, q) models; (v) Identify the optimal number of lags p and q using information critera, such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC); (vi) Predict the value of the economic indicators in 2009 and 2010. TABLE III presents the optimal ARIMA(p, l, q) models and the predicted values in 2009 and 2010 for each economic indicators.[3]

D. Assessments of Economic Risks with Fuzzy Optimization

To examine the variation of economic risks over time, we assign 12 economic indicators in one particular quarter to a group, i.e., each domain of discourse in a fuzzy optimization problem consists of 12 variables. Thus we obtain 40 sets of

[3]Because interest rates are set by the People's Bank of China and exhibit very little variation during the sample period, they are not modeled as an ARIMA process.

TABLE III
FORECASTS FOR KEY EWS INDICATORS IN 2009 AND 2010 USING ARIMA MODELS

Economic indicator	Model	2009	2010
Real interest rate	-	0	0
Inflation rate	ARIMA(2,0,0)	0.6965	0.6347
Real exchange rate	ARIMA(1,0,1)	0.5432	0.5405
FDI/Foreign debt	ARIMA(4,0,0)	0.3764	0.3793
Debt/GDP	ARIMA(1,0,0)	0.2131	0.2093
FDI/GDP	ARIMA(1,0,0)	0.3241	0.3417
Real GDP growth rate	ARIMA(1,0,0)	0.6295	0.6550
M2 growth rate	ARIMA(1,0,0)	0.5916	0.4947
Balance of trade/GDP	ARIMA(4,1,0)	0.2767	0.3074
Foreign exchange reserves/GDP	ARIMA(4,1,0)	0.0589	0.0100
Budget balance/GDP	ARIMA(4,0,0)	0.2450	0.2482
Stock price index	ARIMA(1,0,0)	0.7684	0.6415

EWS indicators between 1999 and 2008. We then compute the matrix of optimal relative membership grade and classify the outputs based on five levels of risks, namely, lowest risk, lower risk, medium risk, higher risk and highest risk. TABLE IV presents computational results and our assessment of economic risks in China.

Figure 3 plots optimal relative membership grade for each quarter during 1999 and 2008. As shown in the table and figure, the level of economic risk before the 2^{nd} quarter of 2002 is relatively low. The rapid economic growth during the periods between 2002-2004 and 2005-2007 are accompanied by accelerated increases in macroeconomic and financial risks. However, in the aftermath of the recent global financial crisis and world-wide recessions, it appears that economic risks in China have somewhat abated. Therefore, it is of interest to see whether the level of economic risks is likely to continue to recede in 2009 and 2010, or it is more likely to turn around and shoot up again.

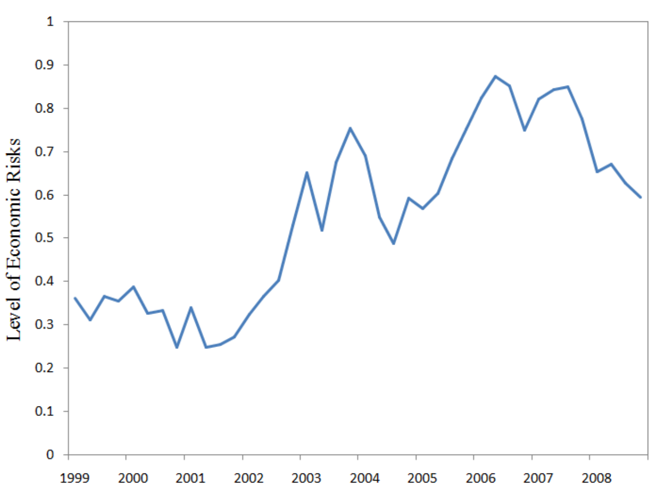

Fig. 3. Variation of Economic Risks in China (1999-2008)

E. Predicting Economic Crises Based on ANN

We select 4 sets of cross-section data as the testing sample, including the 1^{st} quarter of 2005, the 2^{nd} quarter of 2006, the

TABLE IV
ASSESSMENTS OF ECONOMIC RISKS IN CHINA DURING 1999 AND 2008 WITH FUZZY OPTIMIZATION

Year	Quarter	Relative Membership	Level of Risk
1999	1	0.362697	Lower
1999	2	0.311651	Lower
1999	3	0.366939	Lower
1999	4	0.355888	Lower
2000	1	0.388064	Lower
2000	2	0.327072	Lower
2000	3	0.332556	Lower
2000	4	0.248783	Lower
2001	1	0.339471	Lower
2001	2	0.249309	Lower
2001	3	0.25464	Lower
2001	4	0.27319	Lower
2002	1	0.325221	Lower
2002	2	0.366812	Lower
2002	3	0.404262	Medium
2002	4	0.529782	Medium
2003	1	0.651782	Higher
2003	2	0.519424	Medium
2003	3	0.67527	Higher
2003	4	0.754237	Higher
2004	1	0.690039	Higher
2004	2	0.54893	Medium
2004	3	0.487595	Medium
2004	4	0.59299	Medium
2005	1	0.567832	Medium
2005	2	0.602609	Higher
2005	3	0.683741	Higher
2005	4	0.750903	Higher
2006	1	0.822622	Highest
2006	2	0.87478	Highest
2006	3	0.851133	Highest
2006	4	0.748875	Higher
2007	1	0.821767	Highest
2007	2	0.843498	Highest
2007	3	0.849463	Highest
2007	4	0.776677	Higher
2008	1	0.652829	Higher
2008	2	0.670203	Higher
2008	3	0.627697	Higher
2008	4	0.594201	Medium

3^{rd} quarter of 2007 and the 4^{th} quarter of 2008. We use the remaining 36 sets of cross-section data as the training sample, i.e., inputs of neural networks, and denote the output vector as (10000), (01000), (00100), (00010) and (00001), representing lowest risk, lower risk, medium risk, higher risk and highest risk obtained from fuzzy optimization, respectively.

We then construct the BP neural networks using the MATLAB software. After repeated trials, we decide to choose 3 layers for the neural networks. As such, the structure of the BP neural network becomes 12-10-5. Given that the actual output takes the value of either 0 or 1, we use the $tansig$ function as the active function of the hidden layer and the $logsig$ function as the active function of the output layer. In addition, we specify $Trainlm$ as the training function and $Learngdm$ as the threshold learning function and network weight function. Moreover, we choose the MSE command for the performance function and set the learning rate, the momentum constant and the acceptable standard error to be 0.05, 0.9 and $1e^{-6}$, respectively.

Using the aforementioned 36 sets of cross-section data as inputs to the ANN model, we find that the training process stops after 66 trials when the standard error falls below $1e^{-6}$. Using 4 sets of cross-section data as the testing sample, we find that the MSE for the trained neural network is 0.0999, indicating that the mean squared error of our forecasts is within an acceptable range. TABLE V presents the trained results from BP neural networks for 2009 and 2010. As shown in the table, the level of macroeconomic and financial risks in the Chinese economy is predicted to be high, and the likelihood of a full-blown economic crisis remains high in 2010.

TABLE V
PREDICTING ECONOMIC CRISES IN CHINA BASED ON ANN

Year	Output	ANN Outcome	Prediction
2009	(0,0,0,1,0)	(00010)	Higher risk
2010	(0,0,0.001,1,0)	(00010)	Higher risk

IV. CONCLUSION

This paper develops a hybrid intelligent EWS for predicting economic crises. Our hybrid EWS is built on three components—ARIMA models for forecasting individual EWS indicators; fuzzy optimization for assessing various economic and financial risks; and ANN models for predicting the likelihood of economic crises. It integrates the advantages of all three methods combined and can deal more powerfully with issues like fast-learning, uncertainty, adaptability, vulnerability, knowledge capability, and hierarchical solution. Using quarterly data on 12 key macroeconomic and financial indicators of Chinese economy during 1999 and 2008, we find that the in-sample predictive power of our hybrid intelligent EWS is quite reasonable. Our out-of-sample forecasts indicate that the Chinese economy remains at high risk for large-scale economic crises in 2009 and 2010.

Although we have obtained some interesting results, we are aware that prediction in a complex and dynamic social system is indeed a very difficult task that calls upon more advanced and sophisticated techniques of computational intelligence. In addition, how to incorporate qualitative data such as contagion, political disturbances, moral hazard, and herding behavior into intelligent decision support systems remain an open question. We hope to conduct more research in this area in the future.

ACKNOWLEDGMENT

The authors would like to acknowledge financial supports from the National Natural Science Foundation of China (Grant No. 70572065 and 70972081), China Ministry of Education (Grant No. 09YJA790084 and the Program for New Century Excellent Talents in University NCET-08-0614), the Guangdong Pearl River Scholar Fund, the Guangdong Natural Science Foundation (Grant No. 9151063201000050) and the Guangdong Social Science Foundation (Grant No. 09E-16).

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